Determining (s, S) Inventory Policy for Healthcare System: A Case Study of a Hospital in Thailand

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ABSTRACT

In this paper, an (s, S) policy is determined by using a simulation-optimization approach for a periodic review inventory system at a pharmacy department of a major hospital in Thailand. The simulation, which imitates the inventory system behavior, is constructed on a spreadsheet, while the cyclic coordinate method with a golden section search is adopted as the optimization algorithm. Solutions for the policy’s parameters from the search algorithm are evaluated using the simulation, which features randomly generated demand and lead time data from empirical distributions of actual datasets. The objective is to minimize the total inventory cost, including ordering, holding, and shortage costs. This model is applied for 10 medicine items, selected as representatives of the entire item range in the pharmacy department. According to the simulation results, a minimal cost inventory policy for each item is obtained within a short amount of run time. This indicates the effectiveness and efficiency of the proposed approach for this type of problem.

KEYWORDS

Case Study, Cyclic Coordinate Method, Golden Section Search, Intermittent Demand, Inventory Optimization, Long Lead Time, Periodic Review, Spreadsheet Simulation, Stochastic Demand

1. INTRODUCTION

This paper considers an inventory optimization problem commonly found at the pharmacy department of large hospitals in Thailand. Unlike health care systems in some countries, where physicians only give medicine prescriptions and patients then purchase medicines from pharmacy stores, in Thailand all health care systems are one-stop services that prepare medicines and medical supplies for their patients. This characteristic makes inventory management of medicines and medical supplies an essential task in Thailand’s healthcare systems. In such a system, a central stockroom, managed by the pharmacy department, provides medicines and medical supplies (referred to as items in this
paper) to dispensaries and other medical departments (e.g., operation rooms) of the hospital. When item inventory levels become depleted at dispensaries, replenishment orders are placed to the central stockroom. These orders are considered as demand for the central stockroom. Similarly, the central stockroom would place replenishment orders to the suppliers when its inventories become depleted. Effective inventory management at the central stockroom is crucial since it directly impacts the dispensaries and medical department’s ability to serve outpatient and in-patient demands. At the same time, keeping the inventory management cost low is also important. The key to minimizing inventory management cost, while maintaining a service level, is the inventory policy implemented at the central stockroom.

A major hospital, which not only provides real data but also is the industrial user of this study, is typical and representative of the Thai health care system. Currently, the hospital central stockroom uses the $(s, S)$ policy, where a replenishment order is placed to bring the inventory position (IP) to the order-up-to level $S$ when an item’s IP falls on or below the reorder point $s$. Each item at the central stockroom is managed independently regarding how the values of $s$ and $S$ are set. Performance of the central stockroom, therefore, relies on how well these values are determined. Unlike the random demands from in-patients at medical departments and from outpatients at the dispensaries that arrive regularly, demands for an item at the central stockroom are much more variable and intermittent. In addition, the incoming lead times of replenishment items from the suppliers are relatively long and highly variable due to the suppliers’ delivery schedules. Both sources of variability make the problem very challenging.

The shortage of items at the central stock room is handled differently depending on the patient type. In the case of medicine shortage to outpatients, the hospital provides delivery service free-of-charge to the patients as soon as the shortage item becomes available. For in-patients that need the items for their treatment, a shortage is not an option. In such situations, the hospital must arrange special pickup from another nearby health care system or an expedited delivery from the supplier. This type of shortage is considered as a backlog that either can wait (for out-patients) or is immediately fulfilled (for in-patients). Both cases incur backlog costs to the hospital. The backlog cost is considered as a part of the total inventory management cost of the central stockroom, in addition to ordering costs and item holding costs. The objective of the inventory optimization in this healthcare system is, therefore, to determine the inventory policy parameters $(s, S)$ that minimizes the total cost.

Due to the excessive amount of variability in the systems, a simulation-optimization approach to solving this problem is proposed. The approach features a search algorithm that is performed on a simulation model. The simulation component, which captures the system’s random behavior, provides accurate estimates of the system measures of performance, while the optimization component searches for high-quality solutions. Contributions of the paper are two-fold: (1) an effective approach is developed for a typical health care inventory system in Thailand, where demands are highly variable and intermittent and supplier lead times are very long and highly variable, and (2) effectiveness of the proposed approach is demonstrated using a real case study of a large hospital in Thailand.

2. LITERATURE REVIEW

In this section, a review of the literature on previous studies regarding inventory management problems in healthcare industry is presented first. After that, common methods that are applied to determine the solutions for these problems, are discussed. Then, the research gap in the current literature is highlighted.

Managing pharmacy inventories, i.e., medicines and medical supplies, is a major challenge for healthcare decision-makers (Saha & Ray, 2019a). They are generally struggling with the dilemma of having either too much or too little inventory on-hand. On the one hand, holding a low inventory level leads to frequent shortages. This affects the quality of the patient treatment process (Clark,
On the other hand, maintaining a high inventory level results in a large amount of capital being tied up (Maestre et al., 2018). Therefore, healthcare decision-makers are constantly in search of an effective method to manage the inventory such that the responsiveness of their pharmacy department is improved, while the total inventory cost is minimized. Such a method is known as inventory management policy, which governs the operations of an inventory system through a series of parameters that determine the timing and/or the order quantity for an item replenishment order, as well as how often to review the level of inventory. In other words, searching for an effective inventory management method is equivalent to searching for the optimal inventory policy’s parameters. This search has recently been of great interest for Thai healthcare industry, especially hospital (Srizonkhram et al. 2021). In addition to inventory policy, it is important to perform inventory classification and determine optimal service level for items with different characteristics such that the right policy is applied for the right item (Ly & Raweewan, 2021).

To determine the optimal decisions in supply chain problems, an analytical approach is often referred to by many operations researchers (Praneetpholkrang, & Kanjanawattana, 2021). For parameters of an inventory policy, they are analytically determined by the studies of (Çakıcı et al., 2011; Vila-Parrish et al., 2012; Hani et al., 2013; Hajema, 2014; Hovar & Tsadikovich, 2015; Uthayakumar & Karuppasamy, 2017; Chang et al., 2019; Saha & Ray 2019b). The approach allows these authors to model pharmacy inventory problems as mathematical models, from which closed-form expressions for the optimal policy parameters are obtained. Although these expressions provide explicit and rigid instructions on how to effectively operate an inventory system, they are usually complicated to develop and apply in practice (Tiwari & Gavirneni, 2007). In addition to the development and implementation complexity, the analytical approach suffers another issue associated with the use of standard distributions to model the demand of a pharmaceutical product. Indeed, the majority of analytical models often assume that the demand follows either Normal or Poisson distribution. Moreover, these distributions are also used to approximate lead-time demand or demand during protection intervals (Silver et al., 2016). Unfortunately, this assumption and approximation of pharmaceutical demand do not always hold at several pharmacy departments (Zhang et al., 2014), especially the one considered in this study. The demand for many types of medicines and medical supplies in our case are highly fluctuating and intermittent. As a result, the analytical approach is not suitable for problems, where complexities are coupled with uncertainties. To deal with this difficulty, many operations researchers and practitioners resort to another approach, widely known as simulation-optimization (Chiadamrong & Tangchaisuk, 2021).

In this approach, a simulation model is developed to imitate the behaviors of an inventory system. By using the model, the effectiveness of an inventory policy in terms of the total cost can be evaluated. However, since the ranges of policy parameters are relatively large, it would be time-consuming to evaluate all possible combinations of their values. Therefore, a local search algorithm is integrated into the simulation model such that combinations can be evaluated selectively and the knowledge gained from solution evaluations can efficiently guide the search process. This integration significantly reduces the amount of time an algorithm takes to find optimal or near-optimal policy parameters. Several local search algorithms are proposed in the studies of (Zheng & Federgruen, 1991; Fu & Healy, 1997; Kleijnen & Wan, 2007). Generally, the choice of the search algorithm depends on the demand distribution. For instance, (Kleijnen & Wan’s, 2007) algorithms are suitable for continuous distributions, while those from (Zheng & Federgruen, 1991; Fu & Healy, 1997) are favorable for discrete distributions. Because of its capability, simulation-optimization approach has been adopted in several studies, including that of (Shang et al., 2008; Pukcarnon et al., 2014; Rosales et al., 2014; Zhang et al., 2014; Srizonkhram et al. 2021). (Shang et al., 2008) constructs a spreadsheet model to determine the appropriate level of safety stock for a given service level. The study involves the inventory system of GlaxoSmithKline, where the inventory is governed by a periodic review order-up-to (T,S) policy. Both demand and lead time are assumed to be normally distributed. Instead of using a well-known policy, (Pukcarnon et al., 2014) adopt a can-order policy,
which is a variation of (s,S-1,S) policy, for a system of one warehouse and N retailers. The customer demand of each retailer is modeled as a Poisson process. The replenishment lead time is assumed to be negligible. Similarly, (Rosales et al., 2014) develops a hybrid inventory policy, a mix of min-max (s,) S, and continuous review (Q,R), for a large hospital in the Midwest of the U.S. In this model, it is assumed that the demand follows a Poisson process, and the lead time is deterministic. Rather than employing standard distributions similar to (Shang et al., 2008; Pukcarnon et al., 2014; Rosales et al., 2014; Zhang et al., 2014) models the demand as a multimodal empirical distribution. Based on the distribution, the authors implement a spreadsheet model at Kroger’s pharmacy department, in which inventory is managed by using a(n s,S) policy. The policy parameters are determined by adapting a technique proposed by (Fu, Healy, 1997). In a recent study, (Srizontkhram et al. 2021) develop an ARENA simulation model for medium-sized hospital in Thailand. The inventory policy parameters are determined by using Opt-Quest.

Even though simulation-optimization research in pharmacy inventory management has been advanced dramatically in recent years, no study considers lead time uncertainty except that of (Shang et al., 2008). The negligence of variable lead time undermines the effectiveness of the optimal inventory policy because any delay in a shipment may lead to unexpected shortages. Even though stochastic lead time is considered in the study of (Shang et al., 2008), the authors assume a normally distributed lead time, which is rarely true in practice. An eligible distribution for lead time should be non-negative and discrete (Tai et al., 2021). To address the gap in the current literature, uncertain lead time is considered in this study. Specifically, both lead time and demand in our study are assumed to be discrete and empirically distributed.

3. PROBLEM STATEMENT

In this problem, the parameters of the (s,S) policy are determined for a periodic review inventory system using a simulation-optimization approach. As illustrated in Figure 1, the inventory level is monitored on a periodic (i.e., daily) basis. If the inventory level falls on or below a certain threshold, known as reorder point s, an order is placed to raise the inventory position to a specific order-up-to level S.

For the simulation component of the approach, a spreadsheet-based model is developed to capture the inventory system’s behaviors. Since the total inventory cost contains some components, that are

![Figure 1. Periodic review order-up-to level inventory system](image-url)
probabilistic in nature, such as the average inventory on-hand and shortage costs, we need to rely on
simulation rather than conventional analytical methods to evaluate the effectiveness of different
solutions of $s$ and $S$. To search for the solutions of the inventory policy parameters, we resort to
heuristic algorithms. We develop a cyclic coordinate method that features a golden section search
(GSS) algorithm. GSS is an algorithm that does not require any mathematical analysis and is known
to be effective for a system with a complex key performance measure function. However, the GSS
is limited to one-dimensional search, while our problem requires a two-dimensional search. Therefore,
a cyclic coordinate is used to accommodate a two-dimensional search. Descriptions of the simulation
model and method developed in this paper are based on the following notation of the model parameters,
system status, measures of performance, and decision variables.

Index:

$i$: Day index  
$k$: Iteration index

Model parameters:

$d_i$: Demand on day $i$, units  
$l$: Lead time, days  
$W$: Capacity of a delivery package, units  
$C_p$: Ordering Cost, THB/order  
$C_h$: Holding Cost, THB/unit/day  
$C_s$: Shortage Cost, THB/shortage in a unit of the delivery package  
$f(d)$: Empirical distribution of daily demand  
$f(l)$: Empirical distribution of lead time  
$N$: Simulation length, days  
$\varphi$: Golden Ratio, $(\frac{\sqrt{5} - 1}{2})$

System status:

$oh_i$: Beginning inventory on-hand on day $i$, units  
$ip_i$: Beginning inventory position on day $i$, units  
$Q_i$: Order quantity on day $i$, units  
$AQ_i$: Order arrived on day $i$, units  
$\alpha_i$: A binary variable, which takes on a value of 1 if there is an order arriving in day $i$, or
$0$ otherwise.  
$\beta_i$: A binary variable, which takes on a value of 1 if there is an outstanding replenishment order
on day $i$, or 0 otherwise.  
$eoh_i$: Ending inventory on-hand, units  
$eip_i$: Ending inventory position, units

System measures of performance:

$ds_i$: Satisfied demand on day $i$, units  
$s_i$: Shortage on day $i$, units  
$cs_i$: Cumulative shortages on day $i$, units  
$ss_i$: Shortage that can be satisfied on day $i$, units  
$E_p$: Expected ordering, times  
$E_{oh}$: Expected on-hand, units
\( E_s \): Expected shortages, units
\( TC \): Total expected inventory cost, THB
\( TC(X_L) \): Total expected inventory cost of \( X_L \), THB
\( TC(X_U) \): Total expected inventory cost of \( X_U \), THB

Decision variables:
- \( s \): Reorder level, units
- \( S \): Order-up-to level, units
- \( L \): Lower bound, units
- \( U \): Upper bound, units
- \( D \): Differences between upper bound and lower bound multiplied by the golden ratio, units
- \( X_L \): New lower bound, units
- \( X_U \): New upper bound, units

4. MODEL DEVELOPMENT

4.1 Spreadsheet Simulation

In the spreadsheet simulation, the system checks the levels of the beginning inventory on-hand \( oh_i \) and position \( ip_i \). In each period \( i \) (i.e., day), the system places an order under two conditions: if the inventory position is on or below the reorder point \( s \) and there is no outstanding order, i.e., overlapping of replenishment orders is not allowed in the system. An ordering cost \( C_p \) is incurred every time an order is placed. A shortage cost \( C_s \) representing an expedite delivery cost to a patient is charged for every up to \( W \) units of shortage. For example, suppose \( C_s = 35 \) THB and \( W = 20 \). If there is a shortage of \( s_i = 50 \) units on day \( i \). Then, the shortage cost of \( C_s \times \frac{s_i}{W} = 35 \times \frac{50}{20} = 105 \) THB is incurred since this amount of shortage results in three expedited shipments to three different patients. After a random lead time of \( l \), the replenishment order arrives. The arriving inventory will be used to satisfy the cumulative shortage first, and the remaining inventory becomes inventory on-hands to satisfy the demand during the current day. At the end of the day, a holding cost \( C_h \) is applied to every unit of inventory on-hands \( eoh_i \).

Before running the simulation, historical daily demand data of an item and historical lead time data for one fiscal year are fitted with empirical distributions \( f(d) \) and \( f(l) \). To perform a simulation run with a replication length of \( N \) days, demand and lead time data of this length are generated from \( f(d) \) and \( f(l) \). The spreadsheet simulation is constructed by using formulas written in Visual Basic for Applications (VBA). The logic flow of the spreadsheet simulation is shown in Figure 2.

On a given day, the system first updates the arriving order quantity, the beginning on-hand, and the beginning inventory position by using Eqs. (1) – (3):

\[
AQ_i = \begin{cases} 
Q_{i-1} & \text{If } Q_{i-1} > 0 \\
0 & \text{otherwise}
\end{cases}
\]

\( oh_i = \text{Max}\{0, eoh_{i-1} + QA_i - cs_{i-1}\} \) (2)

\( ip_i = Q_i + eip_{i-1} \) (3)
An order of \( Q_i \) is then placed according to Eq. (4), where the conditions for placement are (1) \( eip_{i-1} \leq s \), and (2) there is no outstanding order, \( \beta_i = 0 \). The binary variable \( \beta_i \) that keeps track of whether there is an outstanding order is updated by using Eq. (5). In other words, Eq. (5) specifies that there is an outstanding order if there is an order of \( Q_i \) placed on that day, or if there is an outstanding order from the previous day that has not yet arrived:

\[
Q_i = \begin{cases} 
S - eip_{i-1} & \text{if } eip_{i-1} \leq s \text{ and } \beta_{i-1} = 0 \\
0 & \text{if } \beta_{i-1} = 1
\end{cases}
\tag{4}
\]

\[
\beta_i = \begin{cases} 
1 & \text{if } Q_i > 0 \text{ or } \left( \beta_{i-1} = 1 \text{ and } AQ_i = 0 \right) \\
0 & \text{otherwise}
\end{cases}
\tag{5}
\]

Then, the satisfied demand, shortage, and cumulative shortage are computed by using Eqs. (6)–(8):

\[
ds_i = \min \left\{ d_i, oh_i \right\}
\tag{6}
\]

\[
s_i = \max \left\{ 0, d_i - oh_i \right\}
\tag{7}
\]

\[
cs_i = \max \left\{ 0, cs_{i-1} - AQ_i \right\} + s_i
\tag{8}
\]
To satisfy the cumulative shortage, first, a binary variable $\alpha_i$ is used to keep track of the arriving order on day $i$ as in Eq. (9):

$$\alpha_i = \begin{cases} 1 & \text{if }AQ_i > 0 \\ 0 & \text{if } AQ_i = 0 \end{cases}$$

Then, according to Eq. (10), the cumulative shortage can be satisfied only on the day that there is an order arrival, i.e., $\alpha_i = 1$. A shortage cost $C_s$ representing expedite delivery cost to the patient is charged for every multiple of $W$ units of shortage. That is, the shortage cost is conditional on the capacity of the delivery package and the amount of shortage that can be satisfied:

$$ss_i = \begin{cases} \min(AQ_i, cs_{i-1})/W & \text{if } \alpha_i = 1 \\ 0 & \text{otherwise} \end{cases}$$

At the end of the day, the ending inventory on-hand and inventory position are updated according to Eqs. (11) – (12):

$$eoh_i = \max\{0, oh_i - ds_i - cs_i\}$$

$$eip_i = i p_i - d_i$$

Finally, the system measures of performance and the total cost, which consists of ordering, holding, and shortage costs, are computed at the end of the simulation run according to Eqs. (13) – (16):

$$E_p = \sum_{i=1}^{N} Q_i / S$$

$$E_h = \sum_{i=1}^{N} oh_i / N$$

$$E_s = \sum_{i=1}^{N} ss_i / N$$

$$TC = C_p E_p + NC_h E_h + C_s E_s$$

4.2 Cyclic Coordinate Method With Golden Section Search

The cyclic coordinate method is applied to find the solution of $(s, S)$. The method alternately searches for an optimal (or near-optimal) solution in each coordinate of the solution space (i.e., each variable). For this inventory policy, the solution space has two dimensions, i.e., $s$ and $S$. The method begins the search by fixing $S$, and search for the solution of $s$ that minimizes the total cost. The
initial value of $S$ is set to be the maximum possible value, that is, the maximum value of daily demand multiplied with the maximum value of lead time, and the initial value of $s$ is set to be 1. After finding the solution of $s$, the method turns to search for the new solution of $S$, while fixing the $s$ at the newly found solution. The search keeps alternating until the solution converges.

In each dimension, the GSS is applied to find the solutions that minimize the total cost. Note that the total cost of a given solution of $(s,S)$ is evaluated using the spreadsheet simulation. The GSS starts by initializing a lower bound ($L$), an upper bound ($U$), and a threshold as a terminating criterion, $\varepsilon = 1$. The cyclic coordinate method, which features the GSS, is coded in VBA and proceeds as follows:

**Initialization:** Set the initial value of the order-up-to level $S_0 = d_{\text{max}} \times l_{\text{max}}$, where $d_{\text{max}}$ is the maximum daily demand for the item, and $l_{\text{max}}$ is the maximum lead time, and set the initial reorder point $s_0 = 1$.

Set the golden ratio $\varphi = \left( \sqrt{5} - 1 \right) / 2 = 0.618$.

**Step 1:** Finding the value of $s$, while fixing $S = S_0$:

**Step 1.1:** Set $k = 1$, where $k$ is the iteration number of the GSS.

**Step 1.2:** Set the search boundary of $s$ in the range of $\{ L_k, U_k \} = \text{max} \left\{ 1, 0.9 \times s_0, S_0 - 1 \right\}$.

**Step 1.3:** Compute $D_k$, $X_L$, and $X_U$ using Eqs. (17) – (19), where $\approx$ denotes the rounding to a nearest integer:

\[
D_k \approx (U_k - L_k)\varphi
\]

\[
X_U = L_k + D
\]

\[
X_L = U_k - D
\]

**Step 1.4:** Evaluate two solutions $(X_L, S_0)$ and $(X_U, S_0)$ using the spreadsheet simulation to find their total costs, $TC(X_L)$ and $TC(X_U)$.

**Step 1.5:** Update the search boundary for the next iteration using Eqs. (20) – (21):

\[
L_{k+1} = \begin{cases} 
X_L & \text{If } TC(X_L) > TC(X_U) \\
L_k & \text{If } TC(X_L) < TC(X_U)
\end{cases}
\]

\[
U_{k+1} = \begin{cases} 
U_k & \text{If } TC(X_L) > TC(X_U) \\
X_U & \text{If } TC(X_L) < TC(X_U)
\end{cases}
\]

**Step 1.6:** Set $k = k + 1$. Repeat steps 1.3 to 1.5 until value of the $D_k \leq 1$.

**Step 1.7:** Set $s^* = \begin{cases} 
X_U & \text{If } TC(X_L) > TC(X_U) \\
X_L & \text{If } TC(X_L) < TC(X_U)
\end{cases}$.

**Step 2:** If $s^* = s_0$, then continue to Step 3 and set $s_0 = s^*$. Otherwise, the cyclic coordinate method stops, and the final solution is $(s_0, S_0)$. 
Step 3: Finding the value of $S$, while fixing $s = s_0$:

Step 3.1: Set $k = 1$, where $k$ is the iteration number of the GSS.

Step 3.2: Set the search boundary of $S$ in the range of $\{L_k, U_k\} = \{s_0 + 1.1 \times S_0\}$.

Step 3.3: Compute $D_k$, $X_L$ and $X_U$ using Eqs. (13) – (15).

Step 3.4: Evaluate two solutions $(s_0, X_L)$ and $(s_0, X_U)$ using the spreadsheet simulation to find their total costs, $TC(X_L)$ and $TC(X_U)$.

Step 3.5: Update the search boundary for the next iteration using Eqs. (20) – (21).

Step 3.6: Set $k = k + 1$. Repeat steps 2.3 to 2.5 until value of the $D_k \leq 1$.

Step 3.7: Set $S^* = \begin{cases} X_U & \text{If } TC(X_L) > TC(X_U) \\ X_L & \text{If } TC(X_L) < TC(X_U) \end{cases}$.

Step 4: If $S^* \neq S_0$, then go back to Step 3, and set $S_0 = S^*$. Otherwise, the cyclic coordinate method stops, and the final solution is $(s_0, S^*)$.

In the initialization step, the initial values are set as $(s_0, S_0) = (1, d_{max} \times l_{max})$. In Step 1, the value of $S = S_0$ is fixed, and the GSS is performed to find the value of $s^*$ that results in the minimal total cost for the $(s^*, S_0)$ solution. Two important points should be made, (1) the minimal total cost solution, $(s^*, S_0)$, is obtained from evaluating the solution for $n$ replications of the spreadsheet simulation, each of which has a simulation length of $N$ days, and (2) each solution is evaluated using exactly the same replications of demand and lead time data.

In Step 2 of the cyclic coordinate method, if it appears that the value of $s^*$ is different from its initial value $s_0$, then the final solution has not been found. The value of $s_0$ is updated to be $s^*$, and the cyclic coordinate method turns to search in $S$-dimension. In Step 3, while fixing $s = s_0$, the GSS is performed to find the value of $S^*$ that results in the minimal total cost for the $(s_0, S^*)$ solution. Then, Step 4 checks whether a new $S^*$ is different from the previous initial value $S^*$. If $S^*$ is a new solution, then set $S_0 = S^*$, and the cyclic coordinate method turns to search in $s$-direction. The search is repeated in cycle until the final solution is found, i.e., no change in the solution. It should be noted that the initial boundaries of the GSS, i.e., Step 1.2 and Step 3.2, are adjusted by a factor of 10%. That is, in Step 1.2, the lower bound is set to be 90% of $s_0$ and in Step 3.2, the upper bound is set to be 110% of $S_0$. This adjustment widens the search boundary to ensure that the minimal cost solution is found.

5. Computational Experiment

5.1 Item Classifications

The pharmacy department at the case study hospital carries a total of 1,392 items of medicines and medical supplies. These items are classified using three classification schemes: (1) vital, essential, non-essential (VEN) classification, which is performed by the pharmacists, (2) ABC classification according to annual items total cost, i.e., units of satisfied demand multiplied with unit cost, which vary during the course of the year, and (3) fast-, medium-, and slow-moving (FMS) classification using the item movements for items. Table 1 summarizes the number of items in combination of VEN and ABC classifications.

5.2 Item Selection and Data Collection for the Computational Experiment

Ten items are selected as representatives to demonstrate the proposed simulation-optimization approach. These items are chosen by the management of pharmacy department based on the classification schemes.
According to Table 1, there are only 49 items that belong to the N category. Therefore, the pharmacy department decides to exclude them from the experiment. All other categories in the ABC, VEN, and FMS schemes are included for selection. The data associated with each item, including daily demand, unit cost, selling price, package size, procurement policy, lead time, and expedite delivery cost over three months are collected. Daily demand, lead time are used as the inputs for the simulation model. The unit cost is used to determine the holding cost, while expedite cost and package size are used to estimate shortage cost.

Table 2 contains key summary statistics of each item, including item type, cost parameters, package size, percentage of days with zero demand that indicate the level of intermittency of the demand.

### Table 1. Item classification using VEN and ABC

| Classification | V | E | N | Total |
|----------------|---|---|---|-------|
| A              | 29| 186| 3 | 218   |
| B              | 65| 302| 4 | 371   |
| C              | 126| 635| 42| 803   |
| **Total**      | 220| 1,123| 49| 1,392 |

### Table 2. Summary statistics of 10 representative items

| Item characteristics | Item 1 | Item 2 | Item 3 | Item 4 | Item 5 |
|----------------------|--------|--------|--------|--------|--------|
| Type                 | Tablet | Vial   | Tablet | Vial   | Tablet |
| $C_p$ (THB/order)   | 5      | 5      | 5      | 5      | 5      |
| $C_h$ (THB/day)     | 0.4077 | 0.2723 | 0.1116 | 0.0384 | 0.06712|
| $C_s$ (THB/package) | 40     | 40     | 40     | 40     | 40     |
| $W$ (package size, unit) | 10    | 5      | 10     | 4      | 12     |
| % of zero demand    | 86%    | 86%    | 88%    | 86%    | 87%    |
| $\mu_d$             | 30.13  | 25.29  | 11.81  | 18.29  | 6.43   |
| $\sigma_d$          | 75.72  | 80.15  | 34.39  | 49.53  | 16.13  |
| $CV$                | 2.51   | 3.17   | 2.91   | 2.71   | 2.51   |
| $d_{max}$           | 363    | 400    | 270    | 400    | 120    |
| $d_{min}$           | 2      | 20     | 2      | 20     | 2      |
| $l_{max}$           | 8      | 9      | 10     | 9      | 12     |
| VEN/ABC/FMS         | E/A/Fast | V/C/Slow | E/A/Fast | V/A/Medium | E/B/Medium |

*continued on following page*
item, average and standard deviation of daily demand, coefficient of variation ($cv$), which is the ratio of standard deviation to the average, minimal (excluding zero) and maximal daily demand, maximum lead time, and the item classes. Items’ annual demand, $cv$, and total values (used as bubble’s size) are plotted in Figure 3 to illustrate that the range of items in the hospital is well covered by the selected items.

From the summary statistics, even for the fast-moving items their levels of intermittency are very high. Also, the $cv$, which reflects the levels of uncertainty in the daily demand data, are very high. This is the nature of this system with a small number of customers, i.e., dispensaries and medical departments in the hospital. The replenishment lead times from the suppliers are relatively long, i.e. 1-2 weeks. With the system characteristics that have such high variability, simulation is, therefore, an appropriate tool to capture its dynamic behavior, especially, for the purpose of evaluating inventory policy parameters.

### 5.3 Computational Experiment Setting

In the computational experiment, the demand data and lead time data of each item are fitted with empirical distributions. These distributions are used to randomly generate the demand and lead time data for the simulation. During the run of GSS in the cyclic coordinate method, each solution is evaluated through 20 replications of simulation to estimate the total cost. Each replication length is set to 30,000 days. The number of replications is set by calculating the required sample size such that the half-width of the key measure of performance, i.e., total cost is within 5% of the average value with a confidence level of 95%. In addition, the replication length ($N = 30,000$) is selected to make sure that the system reaches its steady state and that the estimates of the system measures of performance have a good precision. For each item, the initial level of inventory is set at a relatively high level. The warm-up period is set to be at the point when the first replenishment order is placed and the inventory ordering cycle will then repeat.

### 5.4 Numerical Example of Cyclic Coordinate Method

A numerical example of the cyclic coordinate search process is described for item 1 (see Table 3). The maximal lead time and maximal daily demand gives an initial value of $S = 2,904$. In the first
step of the cyclic coordinate method, the value of $S = 2,904$ is fixed, while the GSS finds the value of $s^* = 10$ that minimizes the total cost from 20 simulation replications. In Step 2, since $s$ changes from 1 to 10, the cyclic coordinate method continues to Step 3. In this step, the search for $S$, while fixing $s = 10$, results in $S^* = 110$. Then, the search continues for two more iterations until the final solution $(s^*, S^*) = (45, 110)$ is found. Results of the search process from cyclic coordinate method for the other items are summarized in Table 4.

Finally, Table 5 provides the optimal solutions of all 10 items. The table includes the estimated annual total cost, breakdowns of the total cost, and their proportion as percentages of the total cost. From the results, it is noticed that the first three items have percentage of shortage cost being more dominant than the percentage of inventory holding cost, whereas the opposite is true for Items 4-10. In addition, two

Table 3. Example of cyclic coordinate method Item 1

| Step | Fixing | Golden section search | Total cost |
|------|--------|-----------------------|------------|
| 1    | $S = 2,904$ | $s^* = 10$ | 210,508.60 |
| 2    | Continue to Step 3 | | |
| 3    | $s = 10$ | $S^* = 110$ | 31,071.58 |
| 4    | Continue to Step 1 | | |
| 1    | $S = 110$ | $s^* = 45$ | 31,061.66 |
| 2    | Continue to Step 3 | | |
| 3    | $s = 45$ | $S^* = 110$ | 31,061.66 |
| 4    | Stop | | |

Figure 3. Item coefficient of variation vs. average annual demand

Table 3. Example of cyclic coordinate method Item 1

| Step | Fixing | Golden section search | Total cost |
|------|--------|-----------------------|------------|
| 1    | $S = 2,904$ | $s^* = 10$ | 210,508.60 |
| 2    | Continue to Step 3 | | |
| 3    | $s = 10$ | $S^* = 110$ | 31,071.58 |
| 4    | Continue to Step 1 | | |
| 1    | $S = 110$ | $s^* = 45$ | 31,061.66 |
| 2    | Continue to Step 3 | | |
| 3    | $s = 45$ | $S^* = 110$ | 31,061.66 |
| 4    | Stop | | |
observations regarding the results are, (1) Items 1-3, whose shortage costs have the highest percentage of the total cost, are high-valued items, i.e., they have larger bubble sizes than the other items (see Figure 3), and (2) Items 1 and 3, which have significantly higher percentages of shortage cost than that of Item 2,

Table 4. Search results for Items 2 to 10

| Item 2 | Item 3 | Item 4 |
|--------|--------|--------|
| s      | S      | Total cost | s      | S      | Total cost | s      | S      | Total cost |
| 2      | 3,600  | 177,694.61 | 16     | 2,700  | 102,382.73 | 120    | 3,600  | 26,236.00 |
| 2      | 435    | 40,871.45  | 16     | 80     | 11,045.77  | 120    | 740    | 10,381.06 |
| 135    | 435    | 39,270.50  | 69     | 80     | 10,878.01  | 360    | 740    | 8,004.68  |
| 135    | 260    | 37,549.72  | 69     | 80     | 10,878.01  | 360    | 508    | 7,445.96  |
| 210    | 260    | 36,898.39  |        |        |           | 430    | 508    | 7,291.86  |
| 210    | 250    | 36,887.86  |        |        |           | 430    | 510    | 7,289.54  |
| 210    | 250    | 36,887.86  |        |        |           | 430    | 510    | 7,289.54  |

| Item 5 | Item 6 | Item 7 |
|--------|--------|--------|
| s      | S      | Total cost | s      | S      | Total cost | s      | S      | Total cost |
| 6      | 1,440  | 17,202.65 | 144    | 3300   | 8,968.47  | 9      | 676    | 6,137.52  |
| 6      | 146    | 3,710.71  | 144    | 773    | 3,472.74  | 9      | 109    | 2,311.75  |
| 86     | 146    | 3,199.97  | 374    | 773    | 2,877.17  | 79     | 109    | 1,942.36  |
| 86     | 130    | 3,163.04  | 374    | 502    | 2,466.62  | 79     | 104    | 1,922.42  |
| 89     | 130    | 3,162.17  | 363    | 502    | 2,463.33  | 86     | 104    | 1,921.01  |
| 89     | 130    | 3,162.17  | 363    | 502    | 2,463.33  | 86     | 104    | 1,921.01  |

| Item 8 | Item 9 | Item 10 |
|--------|--------|---------|
| s      | S      | Total cost | s      | S      | Total cost | s      | S      | Total cost |
| 9      | 840    | 5,274.74  | 8      | 360    | 6,031.10  | 15     | 770    | 8,486.09  |
| 9      | 158    | 1,720.48  | 8      | 48     | 1,962.28  | 15     | 95     | 2,493.35  |
| 65     | 158    | 1,478.96  | 27     | 48     | 1,782.47  | 55     | 95     | 2,177.56  |
| 65     | 104    | 1,371.31  | 27     | 43     | 1,772.04  | 55     | 74     | 2,161.19  |
| 73     | 104    | 1,369.10  | 27     | 43     | 1,772.04  | 59     | 74     | 2,156.77  |
| 73     | 110    | 1,354.02  | 8      | 360    | 6,031.10  | 59     | 78     | 2,137.31  |
| 78     | 110    | 1,353.07  |        |        |           | 62     | 80     | 2,128.90  |
| 78     | 110    | 1,353.07  |        |        |           | 62     | 80     | 2,126.62  |
|        |        |           |        |        |           | 64     | 80     | 2,126.62  |
are fast-moving item. This implies that considerable savings can be gained for high-valued, fast-moving items by setting the inventory policy parameters \((s, S)\) lower. The purpose is to reduce the holding cost and to pay the expedite delivery cost for shortage items. This is a reasonable practice in our case because a constant expedite delivery cost is applied for all items regardless of their values.

To further demonstrate the effectiveness of our policy parameters, we conduct a comparison between the existing policy, which is currently used by the pharmacy department at the central stock room, and ours by a simulation. In the current policy, the \(s\) is determined by using three-month moving average of the monthly demand, and the \(S\) is equal to \(s\) multiplying by a factor of 2.5. For illustration purpose, item 2 is arbitrarily chosen and only one replication of the simulation is performed. The comparison results are presented in the following table.

Based on Table 6, it is observed that the pharmacy department manages to keep a large amount of inventory to avoid shortage while our policy results in more balance costs between holding and

| Item | Item 1 | Item 2 | Item 3 | Item 4 | Item 5 |
|------|--------|--------|--------|--------|--------|
| VEN/ABC/FMS | E/A/Fast | V/C/Slow | E/A/Fast | V/A/Medium | E/B/Medium |
| \(s\) (units) | 45 | 210 | 69 | 430 | 89 |
| \(S\) (units) | 110 | 250 | 80 | 510 | 130 |
| TC (THB/Year) | 31,061.66 | 36,887.86 | 15,596.75 | 7,289.54 | 3,162.17 |
| Ordering cost (THB/Year) | 200.42 | 217.25 | 189.76 | 167.33 | 125.39 |
| Holding cost (THB/Year) | 8,195.40 | 15,326.88 | 3,394.75 | 5,616.74 | 1,986.14 |
| Shortage cost (THB/Year) | 22,665.84 | 21,343.74 | 7,293.50 | 1,505.48 | 1,050.64 |
| Ordering cost (% of TC) | 0.65% | 0.59% | 1.74% | 2.30% | 3.97% |
| Holding cost (% of TC) | 26.38% | 41.55% | 31.21% | 77.05% | 62.81% |
| Shortage cost (% of TC) | 72.97% | 57.86% | 67.05% | 20.65% | 33.23% |

| Item | Item 6 | Item 7 | Item 8 | Item 9 | Item 10 |
|------|--------|--------|--------|--------|--------|
| VEN/ABC/FMS | E/B/Slow | E/B/Slow | E/B/Slow | V/C/Slow | E/C/Slow |
| \(s\) (units) | 363 | 86 | 78 | 27 | 64 |
| \(S\) (units) | 502 | 104 | 110 | 43 | 80 |
| TC (THB/Year) | 2,463.33 | 1,921.01 | 1,353.07 | 1,772.04 | 2,126.62 |
| Ordering Cost (THB/Year) | 112.54 | 72.12 | 96.41 | 82.87 | 58.25 |
| Holding Cost (THB/Year) | 1,900.10 | 1,529.93 | 968.14 | 1,345.58 | 1,714.68 |
| Shortage Cost (THB/Year) | 450.68 | 318.96 | 288.52 | 343.59 | 353.69 |
| Ordering cost (% of TC) | 4.57% | 3.75% | 7.12% | 4.68% | 2.74% |
| Holding cost (% of TC) | 77.14% | 79.64% | 71.55% | 75.93% | 80.63% |
| Shortage cost (% of TC) | 18.30% | 16.60% | 21.32% | 19.39% | 16.63% |
shortage. This leads to a significant savings in total annual inventory cost. In addition, since the
inventory system is backlogged one, customer always receive their drugs through express delivery if
these drugs are short. Therefore, the large amount of shortage cost resulted from our policy does not
affect the customer service level. This finding is similar for other items in our experiment.

The finding above implies that for any inventory system with backlog, one needs to evaluate the
trade-off between different cost components to arrive at an effective inventory management strategy.
Specifically, when an item is expensive and in high demand, the item’s holding cost is generally high.
If the expedite delivery cost is relatively lower than the holding cost, it is reasonable to keep a low
level of inventory for that item. This practice should be applied with care, especially in health industry.
For instance, the pharmacy department of many hospitals usually use VEN item classification and
having a low inventory of a high-valued V-class item would be undesirable.

6. CONCLUSION

In this paper, an inventory optimization of a pharmacy department at a case study hospital in Thailand
is considered. A simulation-optimization approach is proposed to find the minimal cost solution of
the $\left( s, S \right)$ policy, currently implemented by the pharmacy department. The approach consists of two
components: (1) the simulation component, which is constructed as a spreadsheet model, for solution
evaluation purposes, and (2) the optimization component, which is based on the cyclic coordinate
method and the golden section search. Ten items are chosen for the computational study. They are
carefully selected such that they can represent the entire line of items in the pharmacy department.
Applying the proposed approach to finding the inventory policies for these items offers promising
results and fundamental insight about managing medicine and medical supply inventories in this case
study. If an item is fast-moving and high-valued, it is cost-effective to keep a low inventory in exchange
for an expedited delivery. This is achieved by setting the inventory policy, i.e., $s$ and $S$, at low levels.
The trade-off observed in our case study still holds for other healthcare inventory systems with similar
operational characteristics.

CONFLICT OF INTEREST

The authors of this publication declare there is no conflict of interest.

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