



**DETERMINING (s, S) INVENTORY POLICY FOR
HEALTH CARE SYSTEM: A CASE STUDY OF
HOSPITAL IN THAILAND**

BY

MR. SORACHAT SAHASOONTARAVUTI

**A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF THE
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MR. SORACHAT SAHASOONTARAVUTI

ENTITLED

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Engineering)

on November 29, 2021

Chairperson



(Associate Professor Parthana Parthanadee, Ph.D.)

Member and Advisor



(Associate Professor Jirachai Buddhakulsomsiri, Ph.D.)

Member



(Assistant Professor Warut Pannakkong, Ph.D.)

Director



(Professor Pruettha Nanakorn, D.Eng.)

Thesis Title	DETERMINING (s, S) INVENTORY POLICY FOR HEALTH CARE SYSTEM: A CASE STUDY OF HOSPITAL IN THAILAND
Author	Mr. Sorachat Sahasoontaravuti
Degree	Master of Engineering (Logistics and Supply Chain Systems Engineering)
Faculty/University	Sirindhorn International Institute of Technology/ Thammasat University
Thesis Advisor	Associate Professor Jirachai Buddhakulsomsiri, Ph.D.
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ABSTRACT

The inventory optimization problems are required an appropriate optimization model. 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 simulation, while the cyclic coordinate method with golden section search is adopted as the optimization algorithm. Solutions from the search algorithm are evaluated using the simulation, which features randomly generated demand and lead time data from empirical distributions of actual data. The objective is to minimize total inventory costs, including ordering, holding, and shortage costs. This model is applied for ten 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 efficiency and effectiveness of the proposed approach for this type of problem.

Keywords: Inventory optimization, Periodic review, Spreadsheet simulation, Stochastic demand, Long lead time, Cyclic coordinate method, Golden section search

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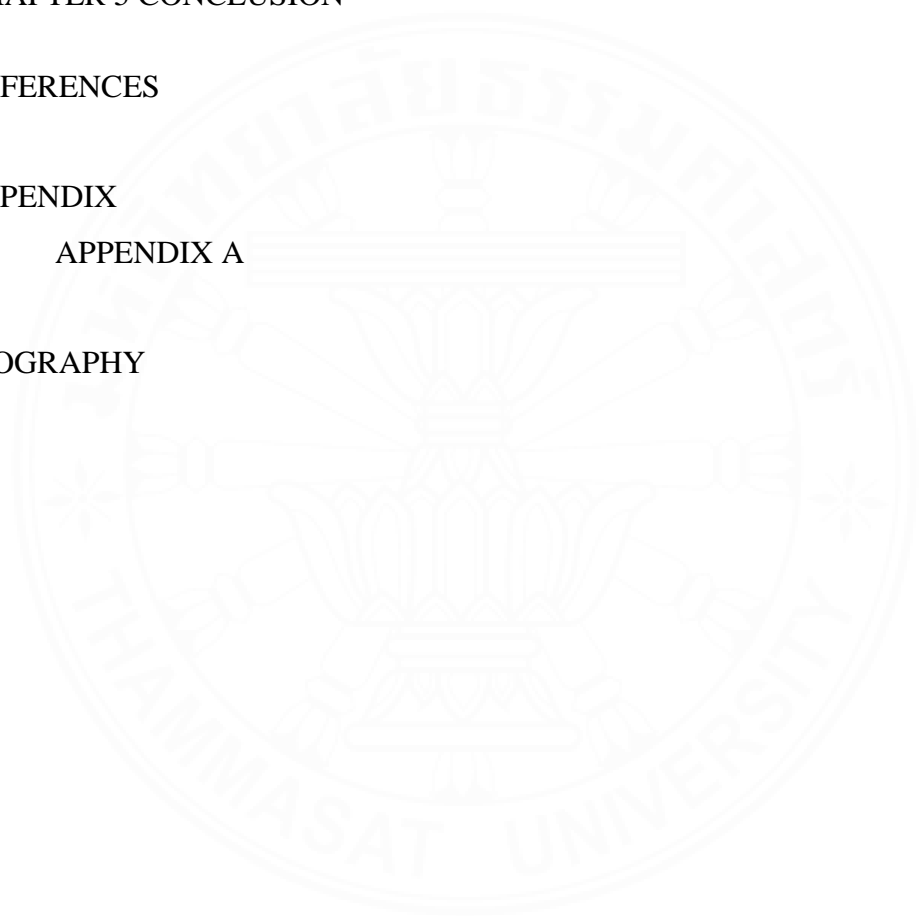
Finally, I would like to thank my parents. They're always taken care of me since I was born. They're keeping supporting me in everything I've done. Without them, I won't be Mr.Sorachat like nowadays.

Mr. Sorachat Sahasoontaravuti

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LIST OF SYMBOLS/ABBREVIATIONS

Symbols/Abbreviations	Terms
i	Day index
k	Iteration index
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
α_i	A binary variable, which takes on a value of 1 if there is an order arriving in day i , order, or 0 otherwise.
β_i	A binary variable, which takes on a value of 1 if there is an outstanding replenishment order on day i , or 0 otherwise.
d_i	Demand on day i , units
ds_i	Satisfied demand on day i , units
l	Lead time, days
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
eah_i	Ending inventory on-hand, units
eip_i	Ending inventory position, units
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 unit of delivery package
E_p	Expected ordering, times
E_{oh}	Expected on-hand, units
E_s	Expected shortages, units
TC	Total expected inventory cost, THB
$f(d)$	Empirical distribution of daily demand
$f(l)$	Empirical distribution of lead time
N	Simulation length, days
ϕ	Golden Ratio, $(\frac{\sqrt{5}-1}{2})$
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
$TC(X_L)$	Total expected inventory cost of X_L , THB
$TC(X_U)$:	Total expected inventory cost of X_U , THB
s	Reorder level, units
S	Order-up-to level, units

CHAPTER 1

INTRODUCTION

The inventory optimization problem is an essential problem in the field of industrial. In a healthcare system e.g., a pharmacy department in a hospital is a center of controlling the drugs transaction system so they are required good management to achieve the patient's demand and the department's costs minimization. Detail of procurement in the medicines ordering could cause the cost in the inventory due to the factor of an extra documentary/frequency in ordering, the holding/over-stocking, and the patient's shortages. In this study we used the real data from in hospital in Thailand to determine the optimality of reorder point and order-up-to level by optimizing the total cost of the inventory, consisting of ordering, holding, and shortage costs from the periodic inventory spreadsheet system simulation with a cyclic coordinate method in an algorithm of golden section search.

1.1 Problem Statement

Phra Nang Klao Hospital is located at Nonthaburi, Thailand in the affiliation of the Ministry of Health. A pharmacy department is located on the Fourth and fifth floors. The fourth floor is where they keep medicines and medical supplements, the production department is on the fifth floor. In this research, we're working on the central drug stock room, where they manage the inventory on the fourth floor. The department diagram is shown in figure 1.1. From figure 1.1, room 1 is an entrance door into the department. The blue boxes in room 1 are refrigerators. Where they keep the vaccine or a specific drug, which is needed a low temperature in a range of 2-8 °C. Room 2 on the left is an office, the pharmacists and staff are working in this room to control the system and document works. Room 3 and room 4. They mainly keep the tablets; it indicates the large portion area of the storage room. Which is the most used type of drug. Room 5 is for specific case drugs and room 6 is used for keeping narcotics, potion, and external drugs. The last room, room 7 is keeping a container or cart for passing an item.

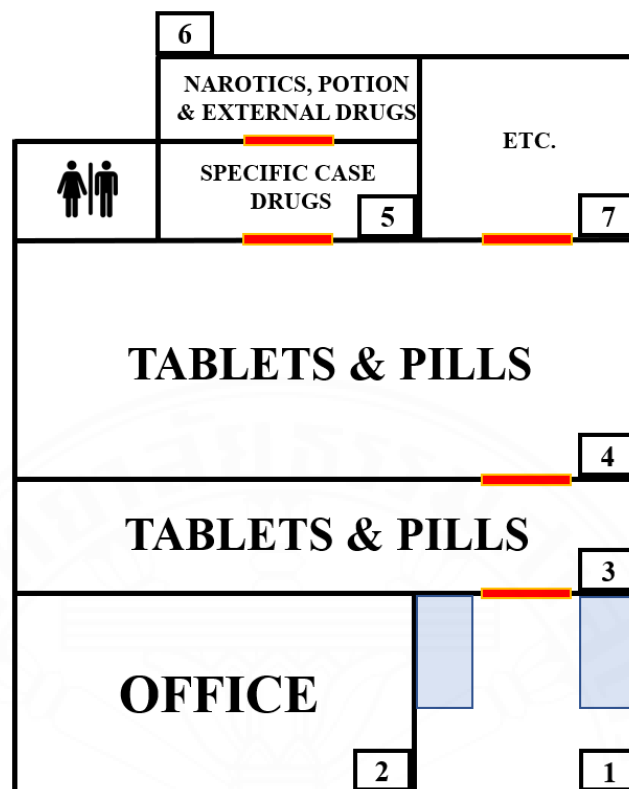


Figure 1.1 Pharmacy Department Diagram

The flowchart of the department where they receive the supplement and dispense to the other units is shown in figure 1.2. A pharmacy department acquires the medicines by purchasing from the supplier, production of the department, donation from health facilities, etc. They dispense the medicines to dispensary room in OPD, IPD, ER, operation room, etc.;

Currently, the department 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 drug storage 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. and will order when the stocks are nearly below the set point.

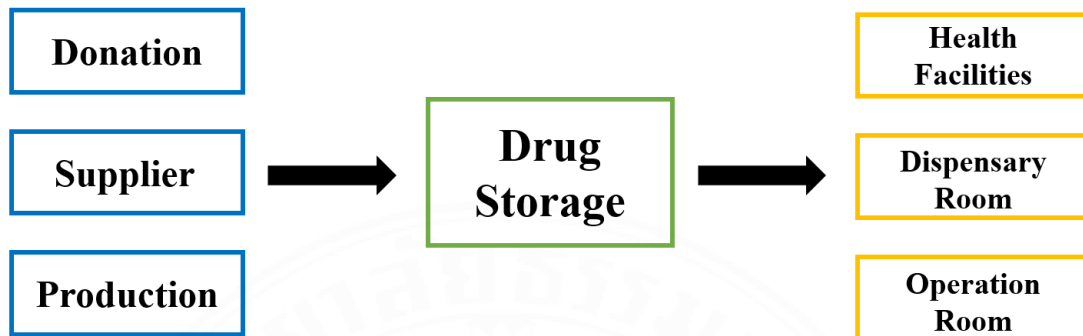


Figure 1.2 Pharmacy Department Flow Chart

1.2 Motivation

Total cost in a pharmacy is depending on many factors of the current problem. Due to the stochastic demand and long lead time could cause an inappropriate reorder point quantity order, which is caused by the lacking of an item, which could make an effect on the patient's safety and cost management problem. Both sources of variability make the problem very challenging. In this research, we would like to determine the order point and order-up-to level for the department by simulating the pharmacy department system.

1.3 Objective

- To Classify the drugs into a group of ABC, VEN, and FMS
- To determine the appropriate quantity of reorder point and order-up-to level point
- To minimize the total cost of the department

1.4 Thesis outline

The composition of this thesis is begun with the review of literature in chapter 2. Where the previous studies were used. Chapter 3 is modeling which is consisting of the drug classification and the simulation system. The contents will expand the detail

of the calculation in a drug classification and the spreadsheet simulation. Chapter 4 is the experiment results and chapter 5 is the conclusion.



CHAPTER 2

REVIEW OF LITERATURE

In this chapter is a literature review from previous studies in the field of inventory management. The literature of this research is consisting of 2 parts. The first part is the method of classifying the drugs and the second part is the background of the inventory optimization system and model development.

2.1 Classification of drugs

The hospital inventories are required for stocking the medication material e.g., a sanitized equipment. Essentially the medicines are carried out for the patients (Maestre, Fernández & Jurado, 2018). Pharmaceutical department really treats the medicines into reliability to satisfy patient's demand (Zepeda, Nyaga & Young, 2016). They found one in a portion of three of annually total cost is spent on the supplies include the medicine (Khurana, Chhillar & Gautam, 2013). Without planning the occasion of supplements and medications material lacking could be occurred and it cost the half of the hospital budget to occupying the material (Holm, Rudis & Wilson, 2015). An existing department resources are numeric and can be utilized with the analysis, a good classification ABC and FMS are required to distinguish the type of the products (Devnani, Gupta & R, 2015). The level of emphasis medicines is also important with the classification calls VEN analysis, which is to distinguish the level (Nadkarni & Ghewari, 2020).

2.2 Model Development

Managing pharmacy inventory, i.e., medicines and medical supplies, is a major challenge for healthcare decision makers (Saha & Ray, 2019a). They are generally struggling with a 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 obviously affects the quality of patient treatment process (Clark, 2012; Saedi, Kundakcioglu & Henry, 2016). On the other hand, maintaining a high inventory level results in a large amount of capital being tied up (Maestre, Fernández & Jurado, 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.

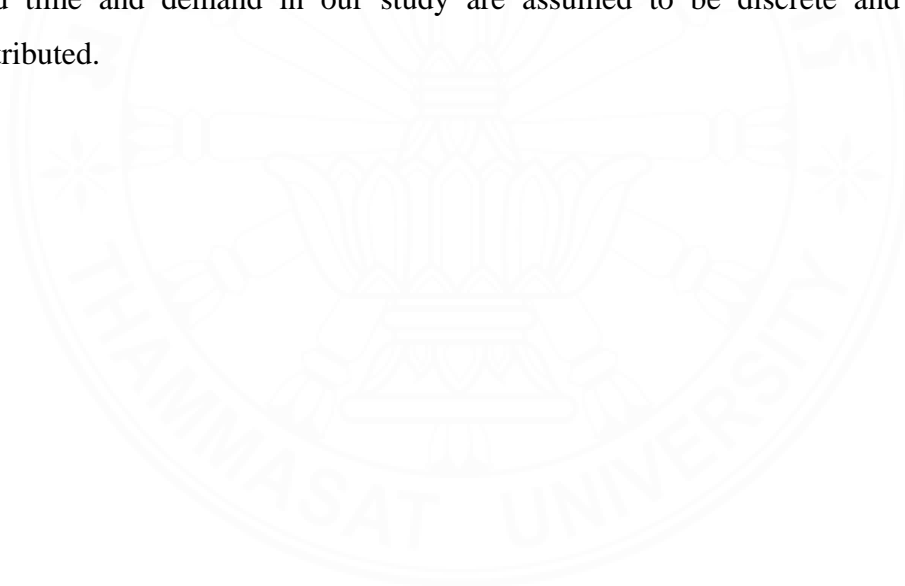
To determine the optimal parameters of an inventory policy, analytical approach is often referred by many operations researchers. For instance, it is adopted in the studies of (Çakıcı, Groenevelt & Seidmann, 2011; Vila-Parrish, Ivy, King & Abel, 2012; Hani, Basri & Winarso, 2013; Haijema, 2014; Hovav & Tsadikovich, 2015; Uthayakumar & Karuppasamy, 2017; Chang, Lu & Shi, 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 and difficult to develop and apply in practice (Tiwari & Gavirneni, 2007). In addition to the development and implementation complexity, 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 interval (Silver, Pyke & Thomas, 2016). Unfortunately, this assumption and approximation of pharmaceutical demand do not always hold at several pharmacy departments (Zhang, Xeiser, Liu, Bonner & Lin, 2014), especially the one considered in this study. In fact, the demand for many types of medicines and medical supplies in our case are highly fluctuating and intermittent. As a result, 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.

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 an 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) and 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, Tadikamalla, Kirsch & Brown, 2008; Pukcarnon, Chaovalitwongse & Phumchusri, 2014; Rosales, Magazine & Rao, 2014; Zhang, Xeiser, Liu, Bonner & Lin, 2014). Shang, Tadikamalla, Kirsch & Brown, (2008) constructs a spreadsheet model to determine the appropriate level of safety stock for a given a 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, Chaovalitwongse & Phumchusri, (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 modelled as Poisson process. The replenishment lead time is assumed to be negligible. Similarly, Rosales, Magazine & Rao, (2014) develops a hybrid inventory policy, a mix of min-max (s, S) and continous review (Q, R) , for a large hospital in the Midwest of 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, Tadikamalla, Kirsch & Brown, 2008; Pukcarnon, Chaovalitwongse & Phumchusri, 2014; Rosales, Magazine & Rao, 2014; Zhang, Xeiser, Liu, Bonner & Lin, 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 (s, S) policy. The policy parameters are determined by adapting a technique proposed by (FU & HEALY, 1997).

Even though simulation-optimization research in pharmacy inventory management has been advanced dramatically in recent years, no study takes lead time uncertainty into consideration except that of (Shang, Tadikamalla, Kirsch & Brown, 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. Eventhough stochastic lead time is considered in the study of (Shang, Tadikamalla, Kirsch & Brown, 2008), the authors assume a normally distributed lead time, which is rarely true in practice. In fact, an eligible distribution for lead time should be non-negative and discrete (Tai, Huyen & Buddhakulsomsiri, 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.



CHAPTER 3

DRUG CLASSIFICATION AND SYSTEM SIMULATION

In this chapter is the main research detail where we demonstrated the system. We divided the section into two parts. The first part is drug classification, the 3 classifications method will be shown in analyzing; ABC, VEN, and FMS. Second part will be the system simulation, the expansion of spreadsheet simulation, and algorithm of Cyclic Coordinate Method with Golden Section Search.

The data we used to operate in this research is from the fiscal year of 2019. Started from October 2018 to September 2019. During that time a pharmacy department carried 1,392 items of medicines and medical supplies. They are consisting of pills, powder, injections, mixture/solution, cream/ointment, inhaler large volume parenteral, etc. As we mentioned above the data, we received from the department. They were demand, lead time, unit price, selling price, policy procurement, and the cost components. The factor components are being applied to the simulation system to determine the research's objectives.

3.1 Drug Classification

The classification is appropriate for the inventory work. To distinguish a level, class, type, etc., good classing leads the system to work easier with utilizing the space and sequence of the products. In this part, we present the 3 methods of classification. Which is using the different factors to analyze.

3.1.1 ABC Classification

An ABC classification is used to classify the annual expenditure of products in each item to organize the items into 3 groups of A, B, and C. Where portion A is in a range of 10-15% of all inventory items and clarifies to 70-75% of total annual expenditure value. B is 20%-25% of all inventory items and clarifies to 15-20% of total annual expenditure. C is 55-60% of all inventory items and clarifies to 5-10% of total expenditure value. To classify the item into a group we use the total expenditure value cumulative and express them into a percentage.

Table 3.1 ABC Analysis

Item No.	Annual Expenditure (THB)	Cumulative Annual Expenditure (THB)	Cumulative Percentage Usage	Class
1	9,131,280.00	9,131,280.00	1.65	A
2	6,891,870.00	16,023,150.00	2.90	A
.
217	691,560.00	412,994,770.08	74.82	A
218	690,145.28	413,684,915.36	74.95	A
.
.
219	682,565.84	414,367,481.20	75.07	B
220	671,478.50	415,038,959.70	75.19	B
.
588	120,054.00	524,259,204.24	94.98	B
589	120,000.00	524,379,204.24	95.00	B
.
.
590	119,700.00	524,498,904.24	95.02	C
591	119,500.00	524,618,404.24	95.04	C
.
1391	0	551,982,720.15	100.00	C
1392	0	551,982,858.21	100.00	C

From the table 3.1, column of annual expenditure shown the expenditure in fiscal year of 2019 in each item and next column, cumulative annual expenditure column is calculated by the cumulative of annual expenditure in each item straightly to the last item. Where we can split the item into the class by the cumulative percentage usage. This column calculates by cumulative annual expenditure in each item divided by total annual expenditure. For example, the percentage of the item No.1 is $\frac{9,131,280.00}{551,982,858.21} = 1.65\%$. The next one, item No.2. the cumulative annual expenditure of

this one is $9,131,280.00 + 6,891,870.00 = 16,023,150.00$ The cumulative percentage usage $\frac{16,023,150.00}{551,982,858.21} = 2.9\%$. We divided an A class to be 75%, B class to be 20%, and C class to be 5% of the total annual expenditure.

Table 3.2 Summary of ABC Classification

Class	Number of Item	% Of Total Item	% Of Value
A	218	15.66	74.95
B	371	26.65	20.05
C	803	57.69	5
Total	1,392	100	100

In a total of 1,392 items. The ABC classification are consisting of, A contents 218 items in 15.66% in total, B contents 371 items in 26.65% in total, and C contents 803 items in 57.69% in total.

3.1.2 VEN Classification

VEN analysis is being used to emphasize the level of each medicine based on the data of the pharmacy department. V is Vital medicine; is a medicine with a high potential for saving a life. Normally used in a fatal specific case. E is an essential medicine; an essential medicine is an important medicine in less severe diseases. This essential drug is not at a level of vital e.g., antibiotic, medicine for a system of heart and blood vessel. N is non-essential me; a non-essential medicine is used for a non-serious case. For VEN classification, we use the data from the pharmacy depart to classify them shown in table 3.3.

Table 3.3 Summary of VEN Classification

Class	Number of Item	% Of Total Item	% Of Value
V	220	15.8	13
E	1,123	80.68	84.86
N	49	3.52	2.14
Total	1,392	100	100

From the table 3.3 The numerous classes are essential drugs, which are contenting 1,123 items in a percentage of 80.98% with an 84.86% in total annual expenditure. For vital drug is 220 items in a percentage of 80.68% with a 13% in total of annual expenditure. Last group, the non-essential drug is 49 items in a percentage of 3.52% with a 2.14% in total annual expenditure

3.1.3 FMS Classification

F, M, and S stand for fast-, medium- and slow-moving. This classification is being applied to determine the frequency of usage. The analysis of FMS can help to reach a problem in inventory management. Where we can identify the movement of the products in an inventory and easy to plan the layout, where we can place a suitable item in positioning, seeing the moving or deadstock of item. E.g., an item with a fast-moving should be in a front of the entrance because it is easy to transfer/transport from place to place, a slow-moving we can identify the lifetime of the product from the frequency of usage with demand and we can also operate an available area for the other item to replace.

Table 3.4 FMS Analysis

Item No.	Annual Dispensed (units)	Consumption Rate (units/day)	Percentage Consumption Rate	Cumulative Percentage Consumption Rate	Class
1	270,429	740.90	9.67%	9.67%	F
2	75,280	206.25	2.69%	12.36%	F
.	
217	5,210	14.27	0.19%	70.64%	F
218	5,105	13.99	0.18%	70.82%	F
.	
.	
219	4,950	13.56	0.18%	71.00%	M
220	4,934	13.52	0.18%	71.17%	M

.	
313	1,410	3.86	0.05%	89.91%	M
314	1,403	3.84	0.05%	89.96%	M
.	
.	
315	1,399	3.83	0.05%	90.01%	S
316	1,397	3.83	0.05%	90.06%	S
.
1391	0	0	0.00%	100.00%	S
1392	0	0	0.00%	100.00%	S

From table 3.4, the consumption rate is used to identify the group of levels for an item movement. Column annual dispensed is the total number of each item that is dispensed out of the department. In column consumption rate is calculated by annual dispensed divided by the number of a year (365 days), so it is shown as a consumption rate a units/day. The summation of the consumption rate is the sum of item 1 to item 1392, which is 7,661.92. The percentage of consumption rate is calculated by the consumption rate in each item number divided by the summation of the consumption rate column. E.g., Item 1; $\frac{740.90}{7,661.92} = 1.65\%$. We sorted a cumulative percentage consumption rate as a class. For fast-moving to be a 70% from a consumption rate, M 20%, and S 10%.

Table 3.5 Summary of FMS Classification

Class	Number of Item	% Of Total Item	% Of Value
F	113	8.12	28.45
M	201	14.44	39.45
S	1078	77.44	32.11
Total	1,392	100	100

A number of fast-moving classify to 113 items in an 8.12% in a total. Medium-moving is 201 items in 14.44% of a total and slow-moving 1078 items in 77.44% of a total. The account value in FMS classification, is 28.45%, 39.45%, and 32.11%.

3.2 Model Development

In this section, we determined the system of the pharmacy inventory system. The department keeps their medicines in grouping them. The working area is needed to control the temperature for 24/7. The important thing is their policy in procurement. The policy and the procurement of the department that used in a fiscal year of 62 told us. In each period of review, a few days in a week. Pharmacists and staff will check the stock in the department. They set the reorder point as a safety stock by use the history of usage ratio in a previous month as 1-month usage, means they will have enough stock to dispense in 1 month. E.g., Item A, assuming usage rate in 1 month is 20 units/day and the stock they have left is 10, 1 month for 30days. The reorder point/safety stock will be $20 \text{ units/day} \times 30 \text{ days} = 600 \text{ units/month}$. It means when the stock reach or nearly to 600 units. Department will order the quantity as the usage rate in 1 month's multiply by 2.5, then minus by the stock. It will be the $(600 \times 2.5) - 10 = 1,490 \text{ units}$, so we determine the policy in the department as a periodic review inventory system (s, S) . They normally receiving the medicines in a Tuesday, Wednesday and Thursday. For dispensing depending on the type of items. For tablets and pills, routinely on Friday, and the other items will be on Friday. If there are emergency cases that occurred except in these two days. The medicines dispensing will be allowed.

Table 3.6 Pharmacy Department Dispensing Routine

Day	Receive	Dispense	Medicine
Monday	-	✓	Others
Tuesday	✓	-	-
Wednesday	✓	-	-
Thursday	✓	-	-
Friday	-	✓	Pills and Tablets

The spreadsheet simulation was built to mimic the pharmacy department inventory system. When we determine two decision variables; reorder point (s), order-up-to level (S). The periodic inventory system (s, S), is an inventory systematic which is review a stock in a period of time to see the stock reach the reorder level (s) and order the quantity of level to S -stock.

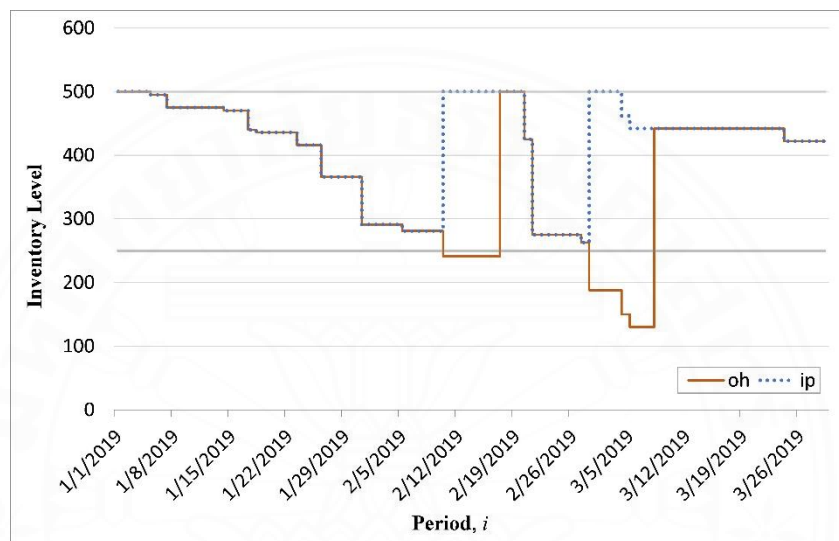


Figure 3.1 (s, S) Simulation System

3.2.1 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 are shortage of $s_i = 50$ units on day i . Then, the shortage cost of $C_s \times \left\lceil \frac{s_i}{W} \right\rceil = 35 \times \left\lceil \frac{50}{20} \right\rceil = 105$ THB is incurred since this amount of shortage incurs three expedite shipment to three different patients. After a random lead time of l , the replenishment order would arrive. The arriving inventory will be used to satisfy the cumulative shortage first, and the remaining inventory becomes inventory on-hands to satisfy the day's demand. At

the end of the day, a holding cost C_h is applied to every unit of inventory on-hands eah_i .

Before running the simulation, historical daily demand data and historical daily lead time data are needed to generate into the empirical distributions as empirical distribution of daily demand $f(d)$ and empirical distribution of lead time $f(l)$ from the probability distribution of them in each item. 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 $f(l)$ in a flow chart in figure 3.2.

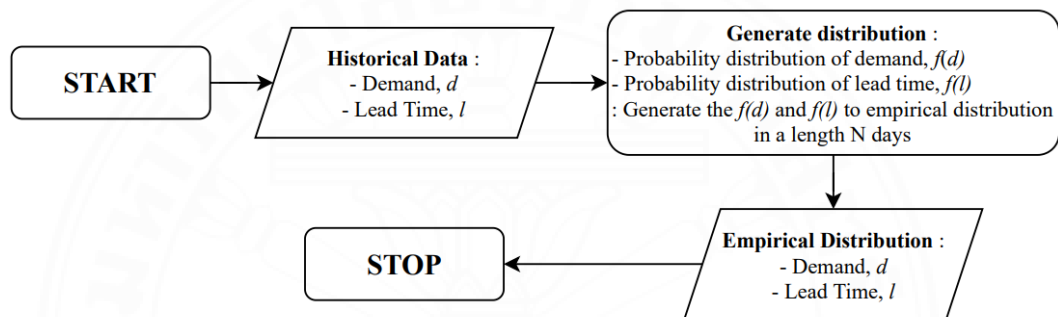


Figure 3.2 Empirical Daily Demand and Lead time Distributions

The spreadsheet simulation is constructed using VBA (Visual Basic for Applications) in Microsoft Excel. Logic flow of the spreadsheet simulation is as shown in Figure 3.3.

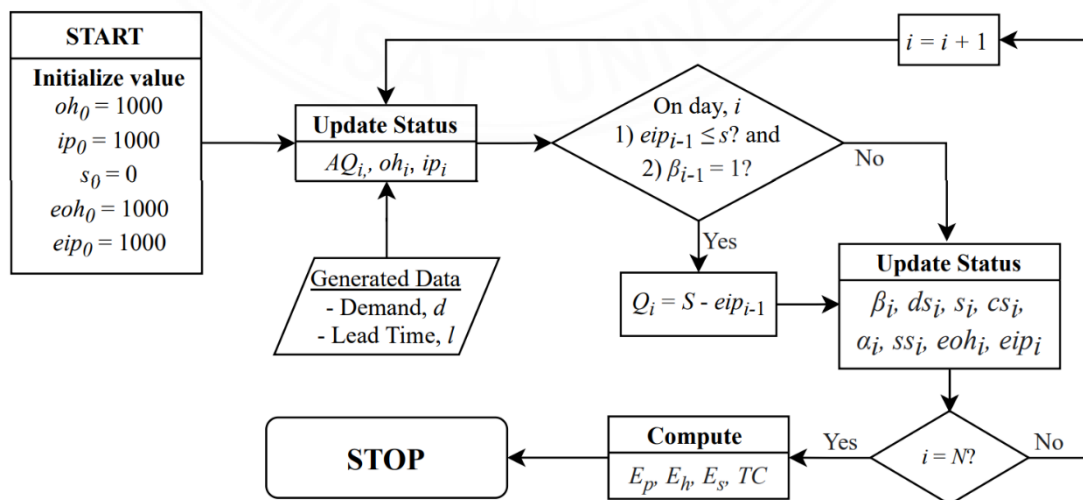


Figure 3.3 Spreadsheet simulation logic flow

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S
1	Day	Beginning OH	Beginning IP	Order	Order arrive	Demand	Overlap Order	Satisfied Demand	No. of shortage	Cumulative shortage	Check SH	LT	Actual SH	Ending OH	Ending IP				
2	0	1000	1000	0			0							1000	1000	s	45		
3	1	1000	1000	0	0	0		0	0	0	0	6	0	1000	1000	S	109		
4	2	1000	1000	0	0	0		0	0	0	0	6	0	1000	1000				
5	3	1000	1000	0	0	0		0	0	0	0	6	0	1000	1000				
6	4	1000	1000	0	0	200	0	200	0	0	0	4	0	800	800	Ordering cost, CP	5	thb/order	
7	5	800	800	0	0	0	0	0	0	0	0	8	0	800	800	Holding cost, CH	0.407743288	thb/day	
8	6	800	800	0	0	0	0	0	0	0	0	5	0	800	800	Shortage cost, CS	-40	thb/10boxes	
9	7	800	800	0	0	0	0	0	0	0	0	4	0	800	800				# of order
10	8	800	800	0	0	0	0	0	0	0	0	6	0	800	800	E(CP)	3,364.00		16,820.00
11	9	800	800	0	0	0	0	0	0	0	0	5	0	800	800	E(OH)	53.73		657,253.23
12	10	800	800	0	0	0	0	0	0	0	0	4	0	800	800	E(S)	49,186.00		1,967,440.00
13	11	800	800	0	0	0	0	0	0	0	0	6	0	800	800				
14	12	800	800	0	0	100	0	100	0	0	0	8	0	700	700	Total Cost	2,641,513.23		
15	13	700	700	0	0	0	0	0	0	0	0	5	0	700	700				

Figure 3.4 Spreadsheet Simulation Interface in Sheet “SM”

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T
1	Demand_1	Demand_2	Demand_3	Demand_4	Demand_5	Demand_6	Demand_7	Demand_8	Demand_9	Demand_10	Demand_11	Demand_12	Demand_13	Demand_14	Demand_15	Demand_16	Demand_17	Demand_18	Demand_19	Demand_20
2	200	100	0	0	0	150	0	0	200	0	0	150	0	0	360	0	0	0	0	0
3	0	100	0	0	203	0	0	0	0	0	100	0	0	0	360	0	0	0	203	0
4	0	0	0	0	0	0	200	0	150	0	0	0	20	0	0	0	0	0	0	0
5	100	0	0	0	0	0	0	0	100	0	0	0	100	100	0	0	0	0	0	200
6	0	0	0	0	0	0	200	0	0	0	360	0	200	0	0	0	0	0	0	0
7	0	0	0	360	0	0	0	0	0	0	0	200	0	0	0	363	0	0	300	0
8	0	0	0	0	0	0	200	0	0	0	0	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10	0	0	200	0	0	0	360	0	360	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	360	0	105	0	0	0	0	0	0	0	0	100	0	100	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	5	200	0	0	0	0	0	0	0	100
14	0	50	200	0	0	0	0	0	0	100	0	0	0	0	0	0	0	363	0	0
15	150	100	0	100	0	0	50	0	150	0	0	0	0	0	0	0	0	0	0	50
16	100	360	0	0	0	0	0	20	0	0	0	5	0	150	100	300	0	0	0	200
17	0	20	0	0	0	0	0	0	0	100	0	0	200	0	0	0	0	0	0	0
18	0	0	100	0	0	0	300	0	100	0	0	0	0	0	100	0	0	0	0	0
19	0	0	0	0	0	360	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Figure 3.5 Empirical Demand Data in Sheet “Demand”

	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T
1	LT_1	LT_2	LT_3	LT_4	LT_5	LT_6	LT_7	LT_8	LT_9	LT_10	LT_11	LT_12	LT_13	LT_14	LT_15	LT_16	LT_17	LT_18	LT_19	LT_20
2	6	4	5	4	4	6	5	5	8	4	4	5	4	4	8	8	5	4	8	6
3	4	4	8	6	5	4	5	6	4	6	8	4	4	4	4	6	4	8	8	6
4	4	6	6	8	4	8	5	4	8	4	5	6	8	4	6	8	5	4	4	6
5	5	4	6	6	4	5	6	8	4	5	8	4	4	4	8	8	5	4	8	4
6	8	5	4	4	8	8	4	8	4	5	6	4	5	5	5	4	5	4	8	8
7	6	6	4	5	6	4	6	5	8	4	4	6	4	5	5	5	8	5	8	5
8	5	4	5	5	5	8	4	4	8	4	5	5	4	4	6	4	6	4	6	4
9	6	8	4	6	6	6	8	8	5	6	4	5	4	4	4	8	5	5	4	6
10	4	4	6	6	8	4	4	6	4	4	8	4	4	4	8	8	4	5	8	5
11	5	4	4	4	6	4	6	5	4	4	8	4	4	4	8	5	8	6	4	4
12	4	4	6	4	8	5	4	8	4	8	4	4	6	4	5	6	4	4	5	6
13	5	8	6	5	5	5	5	4	4	4	4	4	4	4	6	8	4	6	8	8
14	8	5	8	5	4	4	6	8	5	8	4	4	5	8	8	4	6	6	5	5
15	4	5	8	4	4	5	4	4	6	5	8	6	6	4	4	5	4	5	8	4
16	4	5	5	6	4	4	6	5	8	5	6	8	4	5	4	6	6	4	6	6
17	5	6	6	8	4	8	4	6	6	4	6	5	4	4	8	4	5	4	5	5
18	4	6	6	8	4	4	6	8	6	8	4	4	5	4	8	4	8	6	8	4
19	4	5	4	6	8	4	6	4	4	6	6	6	8	8	5	8	5	8	6	6

Figure 3.6 Empirical Demand Data in Sheet “LT”

In figure 3.4 the spreadsheet started from column A to S from row 1 to 30,002. This means a given day on this simulation is run in 30,000 days. The simulation is computed by 2 inputs of column F “Demand” and L “LT (Lead Time)” which is imported from the other sheet “Demand” and “LT” sheets in figure 3.5 and 3.6. The simulation in sheet “SM” starts from column A, “Day” represents the day running through the simulation. Column B, “Beginning OH” is Beginning on-hand. Where the number of products has left in current day. Also, in column C, “Beginning Inventory

Position” The number of products has left in the IP current d”. ay. In ordering column D, “Order” and column L, “Overlap Order. Two of the columns are related. An overlap order column is built for checking the overlapping order by putting the if condition. The system will not order when the overlapping is equal to 1. Otherwise, it equals 0 it will check the Ending IP if it is less than or equal to the setting value of s (as it sets in cell Q2). The system will order the amount equal to the setting value of S (as it sets in cell Q3) minus with Ending IP. Column E, “Order Arrived” depends on order and lead time day counting. Column G, “Satisfied Demand” is the demand that the system can be satisfied using the minimum value of Demand or Beginning OH. Next to is shortage calculation in column H by using the minimum of 0 or Demand minus by Beginning OH. Followed by column I, “Cumulative Shortage” will find the value of cumulative shortage by using the maximum of 0 or cumulative shortage in the day before minus the order arrived in the current day and at the end of maximum value, it will add shortage in current day. Move to the “Ending OH” in column J is how many products the system has left in the current day. Calculated by using the maximum value of 0 or Beginning OH minus Satisfied Demand minus Cumulative Shortage. The final column of system column K, “Ending IP” is checking the point of inventory position at the end of the day by using the value of Beginning IP minus Satisfied Demand minus Shortage.

In this simulation. There are 2 decision variables. s and S in cell Q2 and Q3. The cost of the simulation depends on these 2 variables and it will be searching in the setting boundary and observing total inventory cost. The value of s and S will be selected which is the optimal value that gives the lowest total cost. The total cost in cell Q14 is consists of ordering cost, holding cost, and shortage cost. Ordering cost calculated by the number of orders in cell Q10 multiple with ordering cost per time in cell Q6. Holding cost calculated by the average of Beginning OH in cell O11 multiple with holding cost / day and shortage cost calculate by number of shortages occurred in cell multiple with the shortage.

To be more understanding in a mathematic equations form. All of the conditions mentioned above is demonstrated on the equal of (3.1-3.16). On a given day, the system first updates the arriving order quantity, the beginning on-hand, and the beginning inventory position using Eq. (3.1-3.3).

$$AQ_i = \begin{cases} Q_{i-1} & \text{If } Q_{i-1} > 0 \\ 0 & \text{otherwise} \end{cases} \quad (3.1)$$

$$oh_i = \text{Max}\{0, eoh_{i-1} + QA_i - cs_{i-1}\} \quad (3.2)$$

$$ip_i = Q_i + eip_{i-1} \quad (3.3)$$

An order of Q_i is then placed according to Eq. (3.4), where the conditions in which the system will place an order are, (1) if $eip_{i-1} \leq s$, and (2) there is no outstanding order, $\beta_i = 0$. The binary variable β_i that keeps track of whether or not there is an outstanding order is updated using Eq. (3.5). Simply, Eq. (3.5) 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.

$$Q_i = \begin{cases} S - eip_{i-1} & \text{If } eip_{i-1} \leq s \text{ and } \beta_{i-1} = 0 \\ 0 & \text{If } \beta_{i-1} = 1 \end{cases} \quad (3.4)$$

$$\beta_i = \begin{cases} 1 & \text{If } Q_i > 0 \text{ or } ((\beta_{i-1} = 1) \text{ and } (AQ_i = 0)) \\ 0 & \text{otherwise} \end{cases} \quad (3.5)$$

Then, the demand that can be satisfied, shortage, and cumulative shortage are computed using Eq. (3.6-3.8).

$$ds_i = \text{Min}\{d_i, oh_i\} \quad (3.6)$$

$$s_i = \text{Max}\{0, d_i - oh_i\} \quad (3.7)$$

$$cs_i = \text{Max}\{0, cs_{i-1} - AQ_i\} + s_i \quad (3.8)$$

To satisfy the cumulative shortage, first, a binary variable α_i will keep track of the order arrival on day i , in Eq. (3.9).

$$\alpha_i = \begin{cases} 1 & \text{If } AQ_i > 0 \\ 0 & \text{If } AQ_i = 0 \end{cases} \quad (3.9)$$

Then, according to Eq. (3.10), 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 patient is charged for every multiple of W units of shortage. That is, the shortage cost is conditional on the capacity of delivery package and the amount of shortage that can be satisfied.

$$ss_i = \begin{cases} \left\lceil \frac{\text{Min}(AQ_i, cs_{i-1})}{W} \right\rceil & \text{If } \alpha_i = 1 \\ 0 & \text{otherwise} \end{cases} \quad (3.10)$$

At the end of the day, the ending inventory on-hand and inventory position are updated according to Eq (3.11-3.12),

$$eoh_i = \text{Max}\{0, oh_i - ds_i - cs_i\} \quad (3.11)$$

$$eip_i = ip_i - d_i \quad (3.12)$$

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 Eq. (3.13-3.16).

$$E_p = \sum_{i=1}^N \lfloor Q_i/S \rfloor \quad (3.13)$$

$$E_h = \frac{(\sum_{i=1}^N oh_i)}{N} \quad (3.14)$$

$$E_s = \frac{\sum_{i=1}^N ss_i}{N} \quad (3.15)$$

$$TC = C_p E_p + N C_h E_h + C_s E_s \quad (3.16)$$

3.2.2 Cyclic Coordinate Method with Golden Section Search

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 golden section search is applied to find the solutions that is associated with the minimal value of the total cost function. 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 for stopping 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 $S_0 = d_{max} \times l_{max}$, where d_{max} is the maximum daily demand for the item, and l_{max} is the maximum lead time, and set the initial reorder point $s_0 = 1$.

Set the golden ratio $\varphi = \frac{\sqrt{5}-1}{2} = 0.618$.

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 $\{L_k, U_k\} = \{\max[1, (0.9 \times s_0)], S_0 - 1\}$.

Step 1.3: Compute D_k , X_L and X_U using Eq. (3.17-3.19), where \approx denote rounding to the nearest integer.

$$D_k \approx (U_k - L_k) \varphi \quad (3.17)$$

$$X_U = L_k + D \quad (3.18)$$

$$X_L = U_k - D \quad (3.19)$$

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 Eq. (3.20-3.21).

$$L_{k+1} = \begin{cases} X_L & \text{If } TC(X_L) > TC(X_U) \\ L_k & \text{If } TC(X_L) < TC(X_U) \end{cases} \quad (3.20)$$

$$U_{k+1} = \begin{cases} U_k & \text{If } TC(X_L) > TC(X_U) \\ X_U & \text{If } TC(X_L) < TC(X_U) \end{cases} \quad (3.21)$$

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

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

Step 2: If $s^* \neq s_0$, 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 $\{L_k, U_k\} = \{s_0 + 1, 1.1 \times S_0\}$.

Step 3.3: Compute D_k, X_L and X_U using Eq. (3.17-3.19).

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 Eq. (20-21).

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

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

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_0) .

In the initialization step, the initial values of find the solution of $(s_0, S_0) = (1, d_{max} \times l_{max})$ is set. In Step 1, the value of $S = S_0$ is fixed, and the golden section search is performed to find the value of s^* that results in the *minimal total cost solution*

of the (s^*, S_0) . Two important points should be made, (1) the minimal total cost solution here is based on evaluating the solution for n replications using 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 golden section search is performed to find the value of S^* that results in the minimal total cost of the (s_0, S^*) solution. Then, Step 4 checks whether a new S^* is different from the previous initial value S_0 . If S^* is a new solution, then set $S_0 = S^*$, and the cyclic coordinate method turns to search in s direction. The search repeats in cycle until the final solution is found, i.e., no change in the solution.

Notice that the initial boundary of the golden section search, i.e., Step 1.2 and Step 3.2. The boundary is 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.

CHAPTER 4

RESULTS

4.1 Drug Classification

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) VEN (vital, essential, non-essential) 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) FMS (fast-, medium-, and slow-moving) classification using the item movements for items. Table 4.1 summarizes the number of items in combination of VEN and ABC classifications.

Table 4.1 Item classification using VEN and ABC

Classification	V	E	N	Total
A	29	86	3	218
B	65	302	4	371
C	126	635	2	803
Total	220	1,123	49	1,392

4.2 Item Selection for the Computational Experiment

Ten items are selected as representatives to demonstrate the proposed simulation-optimization approach. Table 4.2 contains key summary statistics of each item, including item type, the three cost parameters, package size, percentage of days with zero demand that indicate the level of intermittency of the item, average and standard deviation of daily demand, coefficient of variation (c.v.), which is the ratio of standard deviation to the average, minimal (excluding zero) and maximal daily demand, maximum lead time, and the item classes. In addition, items' annual demand, c.v., and total values (used as bubble's size) are plotted in Figure 4.1 to illustrate that the 10 selected items are representatives that well cover the range of all items.

Table 4.2 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%
μd	30.13	25.29	11.81	18.29	6.43
σd	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/F	V/C/S	E/A/F	V/A/M	E/B/M

Item characteristics	Item 6	Item 7	Item 8	Item 9	Item 10
Type	Capsule	Cream	Tablet	Ampoule	Vial
C_p (THB/order)	5	5	5	5	5
C_h (THB/day)	0.0144	0.0479	0.0345	0.0863	0.0575
C_s (THB/package)	40	40	40	40	40
W (Package size, unit)	8	6	12	5	2
% Of zero demand	80%	91%	89%	88%	93%
μd	16.17	2.73	3.78	1.49	1.45
σd	38.66	10.78	10.49	4.35	6.71
cv	2.39	3.94	2.77	2.93	4.62
d_{max}	330	52	70	30	70
d_{min}	2	1	2	1	2
l_{max}	10	13	12	12	11
VEN/ABC/FMS	E/B/S	E/B/S	E/B/S	V/C/S	E/C/S

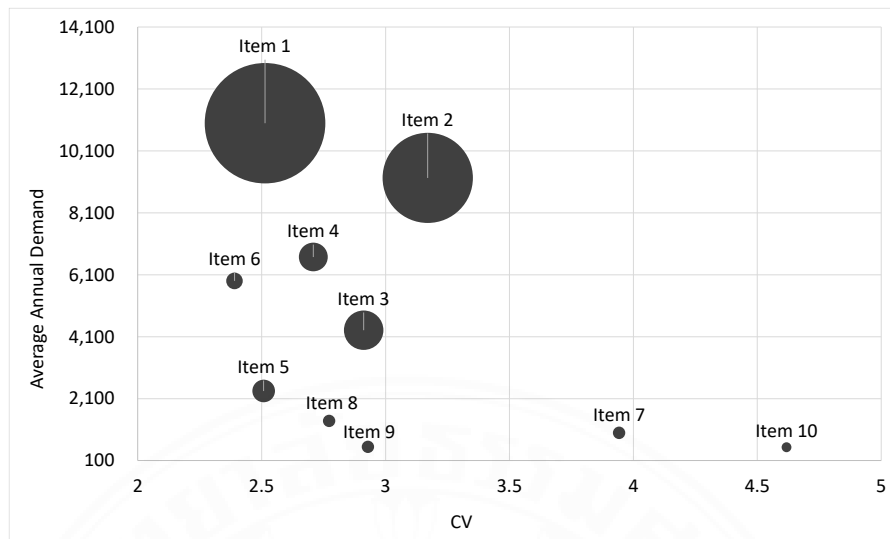


Figure 4.1 Item coefficient of variation vs. average annual demand

From the summary statistics, even for the fast-moving items their levels of intermittency are very high. Also, the c.v., 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 the behavior of the system, especially, for the purpose of evaluating inventory policy parameters.

4.3 Computational Experiment Setting

In the computational experiment, first the demand data and lead time data of each item are fitted with empirical distributions. The distributions are then used to randomly generate the demand and lead time data for the simulation. During the golden section search in the cyclic coordinate method, each solution is evaluated to estimate the total cost using 20 replications. Each replication length is set to 30,000 days. The number of replications is set using a sample size calculation 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 will reach its steady state and that the estimates of the system measures of performance have 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.

4.4 Numerical Example, Experiment Results and Discussion

A numerical example of the cyclic coordinate search process is described for item 1 (see Table 4.3). 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 golden section search 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 Step 3, 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 4.4.

Table 4.3 Results of cyclic coordinate method on the simulation model for 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		

Table 4.4 Search results for Items 2 to 10

Item 2			Item 3			Item 4		
s	S	TC/Year	s	S	TC/Year	s	S	TC/Year

2	3,600	177,694.61
2	435	40,871.45
135	435	39,270.50
135	260	37,549.72
210	260	36,898.39
210	250	36,887.86
210	250	36,887.86

16	2,700	102,382.73
16	80	11,045.77
69	80	10,878.01
69	80	10,878.01

120	3,600	26,236.00
120	740	10,381.06
360	740	8,004.68
360	508	7,445.96
430	508	7,291.86
430	510	7,289.54
430	510	7,289.54

Item 5		
s	S	TC/Year
6	1,440	17,202.65
6	146	3,710.71
86	146	3,199.97
86	130	3,163.04
89	130	3,162.17
89	130	3,162.17

Item 6		
s	S	TC/Year
144	3300	8,968.47
144	773	3,472.74
374	773	2,877.17
374	502	2,466.62
363	502	2,463.33
363	502	2,463.33

Item 7		
s	S	TC/Year
9	676	6,137.52
9	109	2,311.75
79	109	1,942.36
79	104	1,922.42
86	104	1,921.01
86	104	1,921.01

Item 8		
s	S	TC/Year
9	840	5,274.74
9	158	1,720.48
65	158	1,478.96
65	104	1,371.31
73	104	1,369.10
73	110	1,354.02
78	110	1,353.07
78	110	1,353.07

Item 9		
s	S	TC/Year
8	360	6,031.10
8	48	1,962.28
27	48	1,782.47
27	43	1,772.04
27	43	1,772.04
8	360	6,031.10

Item 10		
s	S	TC/Year
15	770	8,486.09
15	95	2,493.35
55	95	2,177.56
55	74	2,161.19
59	74	2,156.77
59	78	2,137.31
62	80	2,128.90
62	80	2,126.62
64	80	2,126.62

Finally, Table 4.3-4.4 provides the final solutions of all 10 items, the estimated annual total cost, breakdowns of the total cost into the three cost components, and then

express each component as percentage of the total cost. From the percentages of the cost components, 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. Two observations regarding the results are, (1) Items 1 to 3 contribute higher in terms of their total value, i.e., they have larger bubble sizes than the other items (see Figure 4.1), and (2) Item 1 and Item 3, which have significantly higher percentage of shortage cost than that of Item 2, are fast-moving item. This implies that considerable savings can be gained for fast-moving items with higher values by setting the inventory policy parameters (s, S) lower. This is to reduce the holding cost and to rather pay the expedite delivery cost for shortage items, which is reasonable because the expedite delivery cost is constant regardless of the item's value.

Table 4.5 Summary of results

Item	Item 1	Item 2	Item 3	Item 4	Item 5
VEN/ABC/FMS	E/A/F	V/C/S	E/A/F	V/A/M	E/B/M
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/S	E/B/S	E/B/S	V/C/S	E/C/S
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%

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.

Table 4.6 Comparison between current and our policies

Policy	(s, S)	Ordering Cost (THB/Year)	Holding Cost (THB/Year)	Shortage Cost (THB/Year)	TC (THB/Year)
Current	(554, 1386)	34.55	89,894.65	1,586.05	91,515.25
Ours	(210, 250)	216.32	15,285.73	21,822.13	37,324.19

Based on Table 4.6, 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 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.

CHAPTER 5

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 (s, S) 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.

Furthermore, of the future study, the classification of items is a base of item selecting decision and the cost minimization can be implement by more complexity of the constraints and more advance technique of simulation algorithm. The difference program or coding language could perform more interesting problems and the outcomes.

REFERENCES

- Çakıcı, Ö. E., Groenevelt, H., & Seidmann, A. (2011). Using RFID for the management of pharmaceutical inventory — system optimization and shrinkage control. *Decision Support Systems*, 51(4), 842-852. doi.org/10.1016/j.dss.2011.02.003.
- Chang, J. A.-C., Lu, H., & Shi, J., J. (2019). Stockout risk of production-inventory systems with compound Poisson demands. *Omega*, 83, 181-198. doi:10.1016/j.omega.2018.03.001
- Clark, M. (2012). Management Sciences for Health. *MDS-3: Managing Access to Medicines and Health Technologies*, Arlington.
- Devnani, Mahesh., Gupta, Ak. & R, Nigah. (2010). ABC and VED Analysis of the Pharmacy Store of a Tertiary Care Teaching, Research and Referral Healthcare Institute of India. *Journal of young pharmacists*, 2(2), 201-5, doi:10.4103/0975-1483.63170
- FU, M. C., & HEALY, K. J. (1997). Techniques for optimization via simulation: an experimental study on an (s, S) inventory system. *IIE Transactions*, 29, 191–199. doi:10.1023/a:1018515011226
- Haijema, R. (2014). Optimal ordering, issuance and disposal policies for inventory management of perishable products. *International Journal of Production Economics*, 159, 158-169. doi:10.1016/j.ijpe.2014.06.014
- Hani, U., Basri, M. H., & Winarso, D. (2013). Inventory Management of Medical Consumables in Public Hospital. *Management Science*, 3(2), 128-133. doi:10.5923/j.mm.20130302.10
- Holm, M., Rudis, M., & Wilson J. (2015). Pharmaceutical supply chain management through implementation of a hospital Pharmacy Computerized Inventory Program (PCIP) in Haiti. *Global health action*, 8, 26546. doi:10.3402/gha.v8.26546
- Hovav, S., & Tsadikovich, D. (2015). A network flow model for inventory management and distribution of influenza vaccines through a healthcare supply chain. *Operations Research for Health Care*, 5, 49-62. doi:10.1016/j.orhc.2015.05.003

- Khurana, S., Chhillar, N. & Gautam, V. (2013). Inventory control techniques in medical stores of a tertiary care neuropsychiatry hospital in Delhi. *Health*, 5, 8-13. doi: 10.4236/health.2013.51002.
- Kleijnen, J. P., & Wan, J. (2007). Optimization of simulated systems: OptQuest and alternatives. *Simulation Modelling Practice and Theory*, 15, 354-362. doi:10.1016/j.simpat.2006.11.001
- Maestre, J. M., Fernández, M. I., & Jurado, I. (2018). An application of economic model predictive control to inventory. *Control Engineering Practice*, 71, 120-128. doi:10.1016/j.conengprac.2017.10.012
- Nadkarni, Rohan. & Ghewari, Asita. (2020). An Inventory Control using ABC Analysis and FSN Analysis. *International Journal of Engineering, Business and Enterprise Applications*.
- Pukcarnon, V., Chaovalitwongse, P., & Phumchusri, N. (2014). The can-order policy for one-warehouse N-retailer inventory system: a heuristic approach. *Engineering Journal*, 18(4), 53-72. doi:10.4186/ej.2014.18.4.53
- Rosales, C. R., Magazine, M., & Rao, U. (2014). Point-of-Use Hybrid Inventory Policy for Hospitals. *Decision Sciences*, 45(5), 913-937. doi:10.1111/deci.12097
- Saedi, S., Kundakcioglu, O. E., & Henry, A. C. (2016). Mitigating the Impact of Drug Shortages for a Healthcare Facility: An Inventory Management Approach. *European Journal of Operational Research*, 251(1), 107-123. doi:10.1016/j.ejor.2015.11.017
- Saha, E., & Ray, P. K. (2019a). Modelling and analysis of healthcare inventory. *OPSEARCH*, 56, 1179–1198. doi:10.1016/j.cie.2019.106051
- Saha, E., & Ray, P. K. (2019b). Patient condition-based medicine inventory management in healthcare systems. *IISE Transactions on Healthcare Systems Engineering*, 9(3), 299-312. doi:10.1080/24725579.2019.1638850
- Shang, J., Tadikamalla, P. R., Kirsch, L. J., & Brown, L. (2008). A decision support system for managing inventory at GlaxoSmithKline. *Decision Support Systems*, 46(1), 1-13. doi:10.1016/j.dss.2008.04.004
- Silver, E.A., Pyke, D.F., & Thomas, D.J. (2016). *Inventory and Production Management in Supply Chains*. CRC Press. <https://doi.org/10.1201/9781315374406>

- Tai, P. D., Huyen, P. P., & Buddhakulsomsiri, J. (2021). A novel modeling approach for a capacitated (S,T) inventory system with backlog under stochastic discrete demand and lead time. *International Journal of Industrial Engineering Computations*, 12(1), 1-14. doi:10.5267/j.ijiec.2020.10.004
- Tiwari, V., & Gavirneni, S. (2007). ASP, The Art and Science of Practice: Recoupling Inventory Control Research and Practice: Guidelines for Achieving Synergy. *Interfaces*, 37(2), 176-186. doi:10.1287/inte.1060.0217
- Uthayakumar, R., & Karuppasamy, S. K. (2017). A Pharmaceutical Inventory Model for Variable Demand and Variable Holding Cost with Partially Backlogged Under Permissible Delay in Payments in Healthcare Industries. *International Journal of Applied and Computational Mathematics*, 3, 1-15. doi:10.1007/s40819-017-0358-9
- Vila-parrish, A. R., Ivy, S. J., King, E. R., & Abel, R. S. (2012). Patient-Based Pharmaceutical Inventory Management: A Two-Stage Inventory and Production Model for Perishable Products with Markovian Demand. *Health Systems*, 1(1), 69-83. doi:10.1057/hs.2012.2
- Zepeda, E. D., Nyaga, G. N., & Young, G. J. (2016), Supply chain risk management and hospital inventory: Effects of system affiliation. *Journal of Operations Management*, 44, 30-47. <https://doi.org/10.1016/j.jom.2016.04.002>
- Zhang, X., Meiser, D., Liu, Y., Bonner, B., & Lin, L. (2014). Kroger Uses Simulation-Optimization to Improve Pharmacy Inventory Management. *Interfaces*, 44(1), 70-84. doi: 10.1287/inte.2013.0724
- Zheng, Y.-S., & Federgruen, A. (1991). Finding Optimal (s, S) Policies Is About As Simple As Evaluating a Single Policy. *Operations Research*, 39(4), 654-665. doi:10.1287/opre.39.4.654



APPENDIX

APPENDIX A

SIMULATION INTERFACE EXAMPLE

	A	B	C	D	E	F	G	H	I
1	S	2904	GR	0.618033989					
2	Loop	A	X2	X1	B	D	Fx1	Fx2	Selected_TC
3	1	1	1109	1795	2903	1794	27,994,613.42	23,789,577.14	23,789,577.14
4	2	1	686	1110	1795	1109	23,791,451.78	21,201,622.82	21,201,622.82
5	3	1	425	686	1110	685	21,201,622.82	19,616,453.57	19,616,453.57
6	4	1	263	424	686	423	19,619,951.71	18,689,813.36	18,689,813.36
7	5	1	163	262	424	261	18,692,404.83	18,179,265.45	18,179,265.45
8	6	1	101	162	262	161	18,180,427.95	17,758,361.00	17,758,361.00
9	7	1	62	101	162	100	17,758,361.00	17,585,938.15	17,585,938.15
10	8	1	39	63	101	62	17,573,182.29	17,494,424.65	17,494,424.65
11	9	1	25	39	63	38	17,494,424.65	17,422,328.42	17,422,328.42
12	10	1	16	24	39	23	17,426,726.38	17,393,312.05	17,393,312.05
13	11	1	10	15	24	14	17,357,616.77	17,302,077.02	17,302,077.02
14	12	1	6	10	15	9	17,302,077.02	17,325,909.43	17,302,077.02
15	13	6	9	12	15	6	17,349,303.37	17,306,120.71	17,306,120.71
16	14	6	8	10	12	4	17,302,077.02	17,320,500.55	17,302,077.02
17	15	8	10	10	12	2	17,302,077.02	17,302,077.02	17,302,077.02
18	16	8	9	9	10	1	17,306,120.71	17,306,120.71	17,306,120.71

Figure A.1 Finding optimal s^* at loop 1

In figure A1 is the example of an item 1 where the maximum demand is 363 and maximum lead time is 8, so the value of the s is 363 multiplied with 8. It equals to 2904 in column B1. At the row 3 is shown the first iteration where the $L_1 = \max[1, 0.9(1)] = 1$ and $U_1 = 2904 - 1 = 2903$, when the boundary was set the new boundary for the iteration will be calculated as L_{k+1} and U_{k+1} as X2 and X1 in column C3 and D3. The total cost of each value will be calculated and place in the column G3 and H3. The value of total cost will be selected from the lowest one of two, the Fx2 is lower than the Fx1 so in the iteration 1 we rejected the boundary of U_1 and continue in the iteration until the value of the $D_k \leq 1$. In this figure the iteration k is stopped at the $k = 16$. The $s^* = 10$, where it got the lowest total cost at 17,302,077.02.

	A	B	C	D	E	F	G	H	I
1	s	10	GR	0.618033989					
2	Loop	A	X2	X1	B	D	Fx1	Fx2	Selected_TC
3	1	11	1227	1978	3194	1967	11,853,997.93	7,412,966.00	7,412,966.00
4	2	11	762	1227	1978	1216	7,412,966.00	4,883,954.83	4,883,954.83
5	3	11	475	763	1227	752	4,882,688.08	3,532,077.76	3,532,077.76
6	4	11	298	476	763	465	3,539,858.03	2,941,898.82	2,941,898.82
7	5	11	189	298	476	287	2,941,898.82	2,691,811.15	2,691,811.15
8	6	11	121	188	298	177	2,684,016.45	2,578,059.84	2,578,059.84
9	7	11	79	120	188	109	2,570,829.79	2,609,672.71	2,570,829.79
10	8	79	121	146	188	67	2,618,283.16	2,578,059.84	2,578,059.84
11	9	79	105	120	146	41	2,570,829.79	2,570,201.79	2,570,201.79
12	10	79	95	104	120	25	2,569,961.37	2,572,699.22	2,569,961.37
13	11	95	105	110	120	15	2,553,828.90	2,570,201.79	2,553,828.90
14	12	105	111	114	120	9	2,587,840.07	2,571,267.64	2,571,267.64
15	13	105	108	111	114	6	2,571,267.64	2,592,264.66	2,571,267.64
16	14	108	110	112	114	4	2,576,522.20	2,553,828.90	2,553,828.90
17	15	108	110	110	112	2	2,553,828.90	2,553,828.90	2,553,828.90
18	16	108	109	109	110	1	2,599,872.78	2,599,872.78	2,599,872.78

Figure A.2 Finding optimal S^* at loop 2

From the figure A2 is shown as the step 3 of finding the optimal value of S , where the optimal value of s^* from the previous calculation is 10. Move forward to the S searching in the range of lower as $L_1 = s_0 + 1 = 10 + 1 = 11$ and upper as $U_1 = 1.1(2904) = 3,194$. Repeat the step of the golden section search until the value of $D_k \leq 1$. It stopped at $k = 16$ where the $S^* = 110$ at the total cost of 2,553,828.90.

	A	B	C	D	E	F	G	H	I
1	S	110	GR	0.618033989					
2	Iteration	A	X2	X1	B	D	Fx1	Fx2	Selected_TC
3	1	9	47	71	109	62	2,553,184.48	2,553,014.03	2,553,014.03
4	2	9	33	47	71	38	2,553,014.03	2,553,558.61	2,553,014.03
5	3	33	48	56	71	23	2,553,277.09	2,553,019.50	2,553,019.50
6	4	33	42	47	56	14	2,553,014.03	2,553,091.67	2,553,014.03
7	5	42	47	51	56	9	2,553,228.45	2,553,014.03	2,553,014.03
8	6	42	45	48	51	6	2,553,019.50	2,553,013.17	2,553,013.17
9	7	42	44	46	48	4	2,553,014.03	2,553,071.14	2,553,014.03
10	8	44	46	46	48	2	2,553,014.03	2,553,014.03	2,553,014.03
11	9	44	45	45	46	1	2,553,013.17	2,553,013.17	2,553,013.17

Figure A.3 Finding optimal s^* at loop 3

Back to find the value of the s where it fits the optimal value of the total cost with the $S^* = 110$, set the $L_1 = \max[1, 0.9(10)] = 9$ and $U_1 = 110 - 1 = 109$. The iteration stops at $k = 9$ where the $s^* = 45$ at the total cost of 2,553,013.17.

	A	B	C	D	E	F	G	H	I
1	s	45	GR	0.618033989					
2	Iteration	A	X2	X1	B	D	Fx1	Fx2	Selected_TC
3	1	46	75	92	121	46	2,561,702.17	2,583,670.49	2,561,702.17
4	2	75	93	103	121	28	2,561,811.44	2,565,006.84	2,561,811.44
5	3	93	104	110	121	17	2,553,013.17	2,569,252.98	2,553,013.17
6	4	104	110	115	121	11	2,579,003.89	2,553,013.17	2,553,013.17
7	5	104	108	111	115	7	2,560,738.19	2,591,606.44	2,560,738.19
8	6	108	111	112	115	4	2,566,213.24	2,560,738.19	2,560,738.19
9	7	108	110	110	112	2	2,553,013.17	2,553,013.17	2,553,013.17
10	8	108	109	109	110	1	2,599,233.24	2,599,233.24	2,599,233.24

Figure A.4 Finding optimal S^* at loop 4

At the final loop of the finding the (s, S) the $s^* = 45$ is set the lower $L_1 = 45 + 1 = 46$ and upper as $U_1 = 1.1(110) = 121$. The iteration stops at $k = 8$ where the total cost is converted with the previous loop 3 at the $S^* = 110$ and $s^* = 45$ with the total cost of 2,553,013.17.

BIOGRAPHY

Name	Mr. Sorachat Sahasoontaravuti
Date of Birth	March 3, 1997
Education	2015: Bachelor of Engineering (Industrial Engineering) Sirindhorn International Institute of Technology Thammasat University

