NON-STERILE M HANDSCOONS INVENTORY CONTROL USING MONTE CARLO SIMULATION: A CASE STUDY

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Abstract

Non-sterile M Handscoons are medical gloves to protect healthcare professionals from transmitting disease through direct patient contact. The handscoons come in boxes at 100 gloves per box. Among all consumable items stocked by Hospital *X*, located in Padang, the handscoons consumed the highest inventory costs. This paper aims to determine a better inventory policy for the Non-sterile M Handscoons. Better order quantity and reorder point were determined. Since the demand for the handscoon was probabilistic, the Monte Carlo simulation was used to determine the order quantity and reorder point to maximize service level and reasonable total inventory costs. The algorithm used to execute the simulation was presented and implemented as a spreadsheet-based Monte Carlo simulation. Four scenarios were compared, combining different order quantities and reorder points, including the hospital's current inventory control policy. A procedure with the mean of service level and total cost as the criteria for selecting the best scenario was presented. The Anderson-Darling Goodness-of-Fit test and Least Squares parameter estimation method showed that the monthly demand follows Weibull distribution with an estimated shape parameter $\hat{\beta}$ = 5.32 and scale parameter $\hat{\alpha}$ = 262.06. The monthly demand mean was 242 boxes. Accordingly, using the Central Limit Theorem, the annual demand was approximately normally distributed, with a mean of 2,899 boxes and a standard deviation of about 178 boxes. The simulation results indicated that an inventory policy with an order quantity of 216 boxes and an order interval of 27 days is the most effective. This policy achieved a mean service level of 99.9 percent with an annual inventory cost of Rp179.35 million. In addition, the selected policy was estimated to guarantee a minimum service level of 94.7 percent and achieved a 100 percent service level with approximately 92 percent certainty. Compared with the status quo, adopting this policy increased the service level by approximately 19 percent, accompanied by a proportional increase in annual inventory costs.

***Keywords*: Cost, Inventory, Simulation**

INTRODUCTION

Hospital *X* is one of the public hospitals located in Padang, Indonesia. The pharmacy department of the hospital manages the inventory of medications and other medical supplies, including medical consumables (BMHP). BMHPs are medical supplies intended for single use, and the government regulates the products list (Regulation of the Minister of Health of the Republic of Indonesia Number 72 of 2016 on Pharmaceutical Service Standards in Hospitals, 2016). At Hospital *X*, there are 270 items on the list.

If BMHP items at Hospital *X* were classified using the ABC method, there were 66 items in A class, with a total cost of around Rp2.5 billion (80 percent), 65 items in B class, with a total cost of around Rp460 million (15 percent), and 139 items in C class, with a total cost of around Rp155 million (5 percent). The above classification was made based on historical data from August 2022 to September 2023. Products in A class must have tighter inventory control and accurate inventory records (Heizer & Render, 2010). Thus, they require more control than products in B and C classes.

Among the 66 items in A class, the non-sterile M Handscoons had the highest cost percentage. Non-sterile M Handscoon is a medical device that is only used once in the form of M-sized gloves. The gloves contain powder to prevent itching. The gloves' primary purpose is to protect healthcare professionals from transmitting disease through direct contact with the patients. From August 2022 to September 2023, the handscoons costed the hospital around 5.52 percent of the BHMP total cost. The hospital consumed about 3,000 boxes of handscoons a year at the price of Rp55,000 a box.

Figure 1 presents the consumption of the handscoons at Hospital *X* from August 2022 to July 2023. Over those 12 months, total consumption was 2,908 boxes, with an average of 242 boxes per month.

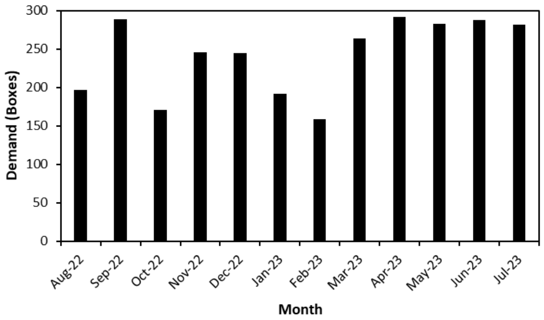

Figure 1. Non-sterile M Handscoons Consumption from August 2022 to July 2023

The hospital policy for handscoon inventory control is that an order will be placed when the stock reaches a level equal to 30 percent of the last three months' consumption. This policy burdened the hospital with high inventory costs. For example, in October 2023, the hospital put in 10 orders. The hospital paid a total of Rp. 199 thousand just for the ordering cost. In July 2023, stock checking showed that the inventory level of the handscoons was 242 boxes and at least they had been in stock for a year. Thus, the hospital paid at least around Rp715 thousand for the interest tied to the handscoons, assuming 5.38 percent interest rate per year.

Most importantly, service level is critical in hospital inventory control because it is directly linked to patient safety, quality of care, and operational reliability. Stockouts of medical supplies, such as handscoons, can interrupt treatments and may even result in legal liability and ethical violations. Unlike commercial settings, hospital prioritize availability and responsiveness rather than purely minimizing inventory cost. Therefore, one of Hospital *X*'s primary objectives is to maximize its service level.

Since the demands for handscoon are probabilistic and do not follow normal distribution, the capabilities of Monte Carlo simulation in optimizing handscoon inventory policy will be exploited. Monte Carlo simulation is a numerical method that uses repeated random sampling to model uncertainty and estimate the behavior and performance of a system. Monte Carlo simulation is widely used because it requires fewer assumptions, flexible and easy to extend, and is suited for what-if scenario.

This paper aims to optimize the inventory policy for Non-Sterile M Handscoon at Hospital *X*. This paper uses Monte Carlo simulation to determine optimal order quantity and reorder point and compares different inventory scenarios. In the simulation, to guarantee optimal service to the patients, maximizing service level is the objective function. The simulation's algorithm is implemented as a spreadsheet-based Monte Carlo simulation. Four scenarios, including the hospital's current inventory control policy, are tested and compared.

LITERATURE REVIEW

Extensive research has been conducted regarding inventory management in the healthcare sector. In this sector, inventory management's primary purposes are to increase service accessibility (Saha & Ray, 2019b), reduce costs (Balkhi et al., 2022), minimize shortage (Bialas et al., 2020), and improve resilience (Friday et al., 2021) to provide affordable healthcare services. However, the healthcare system inventory problem has different characteristics compared to other sectors. Healthcare systems have higher complexity due to diverse inventory items, uncertainty, high service level requirements, perishability, budget constraints, coordination among units, and regulatory compliance (Saha & Ray, 2019b). The difficulties in managing medical supply inventory are highlighted in detail in (Khokhar, 2023).

Due to its complexity, several approaches to managing inventory in the healthcare sector have been proposed. The approaches range from item classification according to their importance, like the ABC classification above (Bialas et al., 2020), mathematical modeling (Shourabizadeh et al., 2023), Just-in-Time (JIT) inventory systems (Balkhi et al., 2022), and the implementation of technologies such as electronic health records (EHR) (Shi et al., 2024) and RFID (Leaven et al., 2017), and practices such as Vendor-Managed inventory (VMI) (Leaven et al., 2017). All approaches aim for better stock monitoring (Khokhar, 2023), improve operational efficiency (González et al., 2023), increase service quality (Balkhi et al., 2022), and ensure optimal patient care (Saha & Ray, 2019a). The literature emphasizes accuracy in forecasting, purchasing, orders, and stock replenishment (Friday et al., 2021).

Monte Carlo simulation is a numerical technique to model uncertainty and risk using repeated random sampling (Kroese et al., 2014). It has been widely used in inventory management. The sectors where Monte Carlo simulation was applied in seeking a better inventory policy were broad, including the micro, small, and medium enterprises (MSMEs), retail, and jewelry production. In the MSME sector, the Monte Carlo simulation was used to determine the optimal order quantity, reorder point, and safety inventory to reduce cost (Domínguez et al., 2024). Monte Carlo simulation was utilized to evaluate order quantity Q and reorder level R scenarios for raw jewelry materials while the demand is stochastic and intermittent (Lathifah et al., 2024). In retail, Monte Carlo simulation was used to find economic order quantity and reorder point under uncertainty in demand and lead time (Leepaitoon & Bunterngchit, 2019). Usually, the simulation was implemented as a spreadsheet.

Spreadsheet-based Monte Carlo simulations to facilitate better inventory control by optimizing order quantity Q and reorder level R can be found in (Lila et al., 2022; Major, 2019). Monte Carlo simulation was also integrated with other optimization techniques to determine a better inventory control policy. Monte Carlo simulation had been coupled with evolutionary algorithm (Widyadana et al., 2017), linear programming (Togo, 2008), dynamic system (Enggar et al., 2022), and artificial intelligence (Preil & Krapp, 2022). However, limited literature applied Monte Carlo simulation in controlling medical supply inventory. It had not been widely, unlike the EOQ, JIT, and periodic review system. This paper fills this gap and uses the Monte Carlo simulation's capabilities to produce a better inventory control policy for a healthcare system.

Some literature highlighted the potential of applying the Monte Carlo simulation in managing medical supply inventory (González et al., 2023), (Preil & Krapp, 2022), (Denny Sentia et al., 2018). Monte Carlo simulation provides several capabilities, such as better handling of uncertainty and variability, enabling modeling of several demands and reorder point scenarios, better risk assessment, and minimizing cost while maintaining service level. Not all of these capabilities are possessed by methods such as item classification, EOQ (Alnahhal et al., 2024), JIT, and mathematical programming.

METHODS

Demand probability distribution determination

In this study, the inventory unit was in boxes of handscoons. One box consists of 100 gloves or 50 pairs. The monthly demand for handscoons was modeled as a random variable. A goodness-of-fit test was conducted to identify the probability distribution that best represents the demand. The Anderson–Darling goodness-of-fit test was employed, and the Anderson–Darling statistic A^2 was computed using equation (1) for each candidate distribution. The candidate probability distributions considered in this study included the exponential, logistic, loglogistic, lognormal, normal, and Weibull distributions. The lower the value of A^2, the better the distribution representing the demand.

$$A^2 = -n - \sum_{t=1}^{n} \left(\frac{2t-1}{n} \left[lnF(D_t) + ln(1 - F(D_{n+1-t})) \right] \right) \quad (1)$$

where,
n = Number of months
t = Month index (t = 1, 2, …, n)
D_t = Demand for handscoons in month t
$F(D_t)$ = The cumulative probability of the demand in month t

$F(D_t)$ is the cumulative distribution function and was evaluated using the estimated distribution parameters. For example, $F(D_t) = 1 - e^{-(D_t/\beta)^{\alpha}}$for Weibull distribution. In this study, the Least Squares method was used for distribution's parameters estimation. The equations employed for parameter estimation are summarized in Table 1.

Table 1. Probability Distribution's Parameters Estimation

Probability distribution	y-coordinate	x-coordinate	Parameter Estimates
Exponential	$\ln[1 - \hat{F}(D_t)]$	t	$\hat{\alpha} = -\frac{1}{m}$
Logistic	$\ln\left[\frac{\hat{F}(D_t)}{1 - \hat{F}(D_t)}\right]$	t	$\hat{\sigma} = \frac{1}{m}$ $\hat{\mu} = -c\hat{\sigma}$
Loglogistic	$\ln\left[\frac{\hat{F}(D_t)}{1 - \hat{F}(D_t)}\right]$	$\ln t$	$\hat{\sigma} = \frac{1}{m}$ $\hat{\mu} = -c\hat{\sigma}$
Lognormal	$\Phi^{-1}\left(\hat{F}(D_t)\right)$	$\ln t$	$\hat{\sigma} = \frac{1}{m}$ $\hat{\mu} = -c\hat{\sigma}$
Normal	$\Phi^{-1}\left(\hat{F}(D_t)\right)$	t	$\hat{\sigma} = \frac{1}{m}$ $\hat{\mu} = -c\hat{\sigma}$
Weibull	$\ln\left[-\ln\left(1 - \hat{F}(D_t)\right)\right]$	$\ln t$	$\hat{\beta} = m$

In Table 1, $\hat{\alpha}$, $\hat{\beta}$, $\hat{\mu}$, and $\hat{\sigma}$ denote the estimated distribution parameters. The terms m and c represent the slope and intercept of the straight line obtained using the Least Squares method. Furthermore, $\hat{F}(D_t) = \frac{t-\frac{1}{2}}{n}$ denotes the estimated cumulative distribution, and Φ^{-1} represents the inverse of the standard normal cumulative distribution. Finally, n is the number of observations.

Scenarios

Two scenarios were evaluated in this study. Scenario 1 represents the status quo, reflecting the hospital's current inventory policy. Scenario 2 represents the proposed policy.

Scenario 1 (*Status Quo*)

The hospital aims to ensure the availability of handscoons for at least three months and assumes that the usage over the most recent three months will be repeated in the near future. Under this policy, an order was placed when the inventory level reaches 30 percent of the total usage during the previous three months, and the order quantity was set to restore the inventory level to 100 percent.

Mathematically, the reorder point for month t, denoted as R_t, is given by equation (2).

$$R_t = (0.3)(D_{t-3} + D_{t-2} + D_{t-1}) \quad (2)$$

To restore the inventory level to 100 percent and ensure sufficient stock for the next three months, the order quantity for month t, denoted by Q_t, is defined in equation (3).

$$Q_t = (0.7)(D_{t-3} + D_{t-2} + D_{t-1}) \quad (3)$$

R_t and Q_t are the decision variables in Scenario 1.

Scenario 2

This scenario adopted a simulation-based evaluation framework within a restricted policy space. Order quantity candidates were derived from the EOQ structure under stochastic demand, and each policy was evaluated using Monte Carlo simulation. The optimal order quantity was selected based on the maximum service level. This approach is consistent with simulation-based optimization methodologies widely applied in stochastic inventory systems (Chu et al., 2015) (Schwartz et al., 2006) and grounded in Monte Carlo sampling-based stochastic optimization theory (Homem-de-Mello & Bayraksan, 2014).

Since D_t is a random variable with a probability distribution identified in the previous section, the annual demand D is also a random variable, defined as the sum of monthly demands over 12 months ($n = 12$).

$$D = \sum_{t=1}^{n} D_t \quad (4)$$

Random annual demand realizations D_j were generated from this distribution. For each realization, the corresponding order quantity Q_j was calculated using equation (5). Thus, there were many values of Q_j.

$$Q_j = \sqrt{\frac{2D_j s}{h}} \quad (5)$$

In equation (5), the ordering cost per order, denoted by s, was estimated based on hospital records and included costs associated with internet usage, telephone calls, administrative activities, and staff wages. The holding cost h was calculated as the cost of capital tied up in inventory. If the annual interest rate is i and the purchase price of a box of handscoons is c, the holding cost per box per month is given by,

$$h = \frac{ic}{12}$$

The restricted policy search was conducted by selecting representative order quantities from the empirical distribution of Q_j, specifically the minimum, mean, and maximum ($Q_{\min}$, Q_{mean}, and $Q_{\max}$,). This selection captured low, mean, and high demand regimes.

The number of orders placed per year and the interval between orders under this scenario are given by equations (6) and (7), respectively,

$$N = \frac{D}{Q} \tag{6}$$

$$T = \frac{365}{N} \tag{7}$$

where N denotes the number of orders per year and T represents the order interval in days. Since there were three Q values, there were three N values ($N_{\min}$, N_{mean}, and $N_{\max}$) and also three T values ($T_{\min}$, T_{mean}, and $T_{\max}$) which correspond to $Q_{\min}$, Q_{mean}, and $Q_{\max}$, respectively. Consequently, there were three variations for Scenario 2: Scenario 2.1 which used $Q_{\min}$, $N_{\min}$, and $T_{\min}$, Scenario 2.2 which used Q_{mean}, N_{mean}, and T_{mean}, and Scenario 2.3 which used $Q_{\max}$, $N_{\max}$, and $T_{\max}$.

The value of T served as the basis for determining the ordering frequency within each month. For example, if T = 24 days, orders were placed on days 24, 48, 72, 96, 120, and so forth. Consequently, in fourth month, two orders were placed because days 96 and 120 fall within the fourth month. The notation t' was used to denote the month in which an order will be placed. Q and t' are the decision variables in Scenario 2. Thus, $Q = 0$, for $t \neq t'$.

Simulation Procedure

Both scenarios were simulated over 12-month ($n = 12$) planning horizon and replicated M times. The decision variables in the simulations are the combination of Q and R that will maximize service level S and minimize total inventory cost TC. The service level S, defined in equation (8), is the ratio between the fulfilled demand and the demand.

$$S = \sum_{j=1}^{M} \sum_{t=1}^{n} \frac{D'_{tj}}{D_{tj}} \tag{8}$$

where,

S = Service level (percent)

D'_{tj} = Fulfilled demand in month t in the jth replication (boxes)

D_{tj}= Demand in month t in the jth replication

The quantity of boxes of handscoons received from the supplier in month t is U_t, given by equation (9).

$$U_t = \begin{cases} Q_t & \text{, for Scenario 1} \\ aQ & \text{, for Scenario 2} \end{cases} \tag{9}$$

where Q_t and Q are given by equations (3) and (5). The variable a is a non-negative integer ($a =$ 0, 1, 2, …) representing the order quantity in month t. This variable is required because the ordering interval is defined in days, which may result in multiple orders being placed within a single month t. In such cases, the total quantity received during the month may be a multiple of the fixed order quantity Q. The variable is needed because there is a possibility that for particular month t', the order quantity is doubled or even tripled. This possibility occurs because the interval of order is in days. The total quantity of boxes received in month t, denoted ad I'_t, is,

$$I'_t = I_t + U_t \tag{10}$$

I_t is the beginning inventory in month t.The fulfilled demand D'_t is defined as the minimum value between I'_t and D_t,

$$D'_t = min\{I'_t, D_t\} \tag{11}$$

Consequently, the ending inventory in month t, denoted as I''_t, is,

$$I''_t = I'_t - D'_t \tag{12}$$

The beginning inventory in month t is the ending inventory in month $t-1$, $I_t = I''_{t-1}$.

In Scenario 1, the decision to place an order in the end of month t is denoted as P_t which takes binary values, 0 for not placing an order and 1 for placing an order. In Scenario 1, P_t depends on the sum of ending inventory and quantity of order in month t, denoted as E_{t-1}, demand fulfilled in month $t$or D_t', and whether the order is placed in month $t-1$, and R_t. P_t and E_t are given by equations (13) and (14).

$$P_t = \begin{cases} 1, & \text{for } E_{t-1} \leq R_t \\ 0, & \text{otherwise} \end{cases} \tag{13}$$

$$E_t = E_{t-1} - D_t{}' + QP_{t-1} \tag{14}$$

When the order is placed in the end of month t, the order will be received in the beginning of month $t+1$.

In Scenario 2, the decision to place and order in month t depends on whether $t = t'$ or not. Therefore,

$$P_t = \begin{cases} 1, & \text{for } t = t' \\ 0, & \text{otherwise} \end{cases} \tag{15}$$

Since the order interval is fixed, the order can be scheduled and arrive in the same month.

In both scenarios, the average of annual inventory costs consists of ordering and holding cost and are given by equation (16).

$$TC = \frac{1}{M}\sum_{j=1}^{M}\sum_{t=1}^{n}\left(cU_{tj} + sP_{tj} + hI_{tj}''\right) \tag{16}$$

Where,

c = Price of a box of handscoons (Rp)

P_{tj} = Decision whether to order in month t in the jth replication

I_{tj}'' = Ending inventory in month t in the jth replication (boxes)

Based on the above model, an algorithm presented in Figure 2 was designed to run the simulation.

The procedure to select the best scenario is the following:

1. Select a scenario producing a higher service level;
2. If there is a tie, select a scenario producing the lowest total inventory cost.

Results and Discussion

Monthly demand data from August 2022 to July 2023 were used to determine the probability distribution of monthly demand. The minimum, mean, maximum, and standard deviation values of the demand were 159, 242.3, 292, and 49.6 boxes, respectively. The results of the Anderson-Darling Goodness-of-fit test are presented in Table 2.

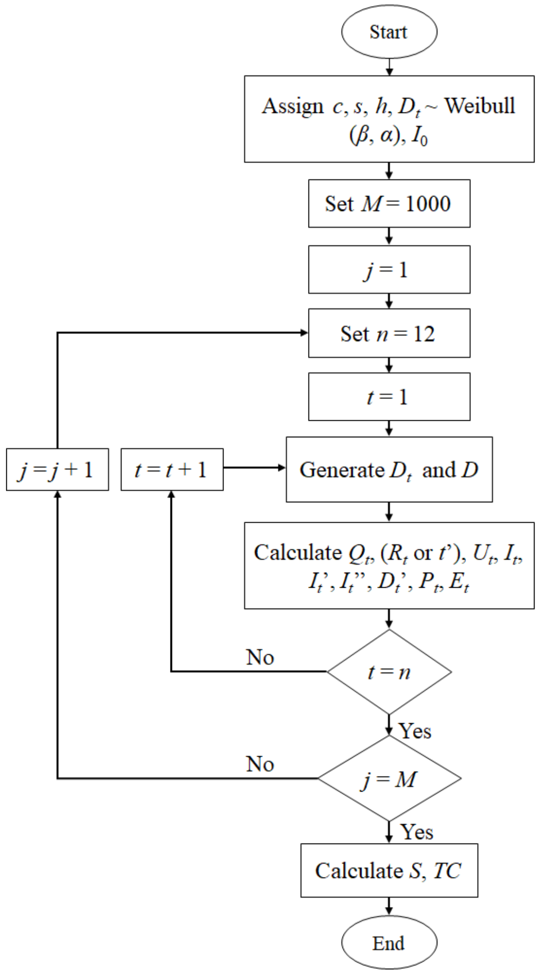

Figure 2. Simulation Algorithms

As shown in Table 2, the Weibull distribution provides the best fit to the monthly demand data, as it yields the lowest Anderson–Darling statistic, (A^2=1.51). The distribution parameters were estimated using the Least Squares method, and the corresponding estimation formulas are presented in Table 1. The estimated shape and scale parameters are $\hat{\beta} = 5.32$ and $\hat{\alpha} = 262.06$, respectively. Accordingly, the monthly demand was modeled as $D_t \sim \text{Weibull}\,(5.32, 262.06)$. The cumulative distribution function of the monthly demand is therefore given by,

$$F(D_t) = 1 - e^{-\left(\frac{D_t}{262.06}\right)^{5.32}}$$

Table 2. Anderson-Darling Goodness-of-fit Test Results

Distribution	Anderson-Darling (A^2)
Exponential	7.29
Logistic	1.72
Loglogistic	1.82
Lognormal	1.72
Normal	1.63
Weibull	1.51

Figure 3a presents the Weibull probability plot of the monthly demand data. The plotted points form an approximately straight line and closely follow the fitted line, indicating an adequate fit, consistent with the Anderson–Darling statistic (A^2= 1.51 > 0.1). Based on the estimated cumulative distribution function $F(D_t)$, a histogram of the monthly demand was generated. The resulting histogram is shown in Figure 3b.

In both scenarios, the initial inventory at the beginning of the first month was set to $I_1 = 242$ boxes, based on the hospital's record at the end of July 2022. The purchasing cost of a box of handscoons was $c = \text{Rp}55$ thousand. The average yearly interest rate in Indonesia from 2022 to 2023 was $i = 5.4$ percent. Accordingly, the holding cost per box per month was calculated as,

$$h = \frac{(0.054)(\text{Rp}55 \text{ thousand})}{12} = \text{Rp}248$$

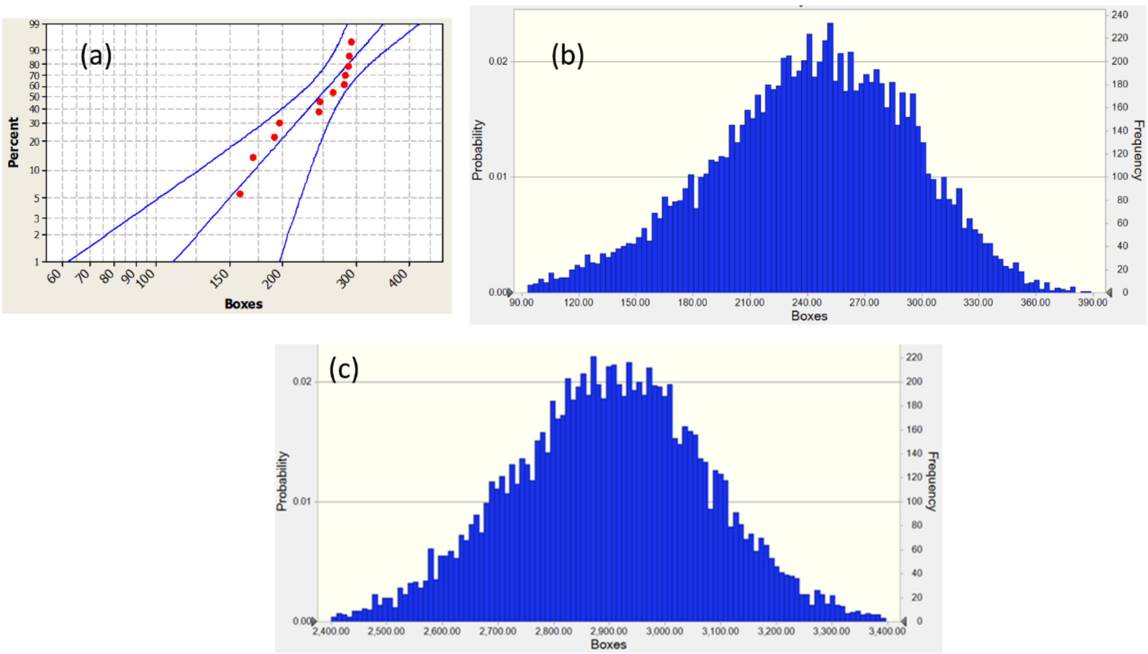

Figure 3. Demand: (a) Probability Plot, (b) Monthly Demand $D_t \sim \text{Weibull}\,(5.32, 262.06)$, (c) Yearly Demand $D \sim \text{Normal}(2{,}898.60\,,\ 177.79^2)$

The ordering cost consisted of internet (Rp129.56), phone call (Rp5,856.00), administrative activities (Rp900.00), and wage (Rp13,041.67) resulted in total ordering cost s = Rp19,927.22 per order.

The above algorithm was then implemented using a spreadsheet-based Monte Carlo simulation. The repeated random sampling was performed using Crystal Ball application. The design of the spreadsheet was based on (Major, 2019). The simulation was run for n = 30 days (one month) and replicated 1000 times (M = 1000).

In Scenario 1, the reorder point for month t, denoted as $R_t$was calculated using equation (2).

The random variables D_{t-3} , D_{t-2}, and D_{t-1} were generated from Weibull distribution, $D_t \sim \text{Weibull}\,(5.316, 262.061)$. A similar method was applied for Q_t, using equation (3). All random variates were generated using the Crystal Ball application. Table 3 presents mean value of Q_t. In Scenario 1, the mean value of the number of orders per year was 5.58 and the interval between orders was around 61 days. Figure 4 presents the histogram of the annual number of orders under Scenario 1.

In Scenario 2, the yearly demand D was defined as the sum of monthly demands over a 12-month period. Since D_t was a random variable, D was also a random variable. By the Central Limit Theorem, D was approximated by a normal distribution. Figure 3c shows the histogram frequency of the yearly demand. The yearly demand has a mean of 2,898.60 boxes and variance of 177.79^2, denoted as $D \sim \text{Normal}(2{,}898.60\,,\ 177.79^2)$. In every replication, D was sampled from $D \sim \text{Normal}(2{,}898.60\,,\ 177.79^2)$ and the value was substituted into equation (5) to obtain the selected order quantity values (Q_{min}, Q_{mean}, and Q_{max}). Table 3 presents the order quantity and the interval between orders under each variation of Scenario 2 (Scenarios 2.1, 2.2, and 2.3).

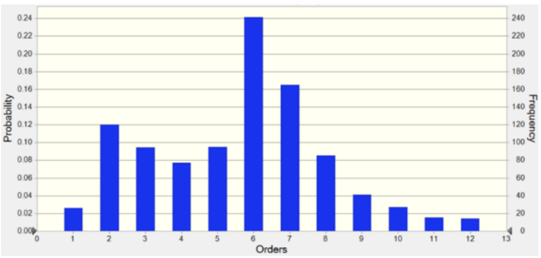

Figure 4. Number of Orders per Year (Scenario 1)

Table 3. Order Quantities

Scenario	Order Quantity Q (boxes)	Interval between Orders T (days)
Scenario 1	507*	61*
Scenario 2.1	176	22
Scenario 2.2	197	24
Scenario 2.3	216	27

**Mean value*

Using equations (6) and (7), the average number of orders per year and time interval between orders were obtained. For example, in Scenario 2.2, $N = (2{,}898.60/197) \sim 15$ orders per year and $T = (365/15) \sim 24$ days. These numbers mean that orders were placed in days number 24, 48, 72, 96, 120, 144, 168, 192, 216, 240, 264, 288, 312, 336, and 360. This result indicates that order must be placed every month but the quantity of orders for months number 4, 8, and 12 was doubled ($a = 2$) because days 96 and 120 are in the fourth month, days 216 and 240 are in the eighth month, and days 336 and 360 are in the twelfth month. Similar approach was applied in Scenario 2.1 and 2.3.

Table 4 summarizes the simulation results. Based on the predefined procedure for selecting the best scenario, Scenario 2.3 was identified as the most favorable option. Scenario 2.3 exhibited the highest mean service level (99.9 percent) and had the narrowest service level range (5.30 percent), indicating both superior performance and greater consistency. The range value also indicates that Scenario 2.3 resulted in at least 94.7 percent service level, the highest among all alternatives.

However, Scenario 2.3 did not have the lowest service level standard deviation. Scenario 2.1 exhibited the lowest service level standard deviation (0.15%), but it guaranteed a minimum service level of only 80.38%. Based on the selection criteria defined in the Methods section, Scenario 2.3 was therefore identified as the best scenario. Figure 5 further supports these findings. The certainty analysis conducted using the Crystal Ball application indicates that Scenario 2.3 achieved a 100% service level with approximately 92% certainty. Scenario 1 followed, with a certainty level of about 21% for achieving a 100% service level. Scenarios 2.1 and 2.2 exhibited relatively low certainty levels (12.3% and 14.3%, respectively) in achieving a 100% service level.

Improvements in service level are generally associated with higher annual inventory costs. As shown in Table 4, Scenario 2.3 incurred the highest annual inventory cost, followed by Scenario 2.2, Scenario 1, and Scenario 2.1. The cost per 1% increase in service level was approximately Rp1.80 million for Scenario 2.3,

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Rp1.65 million for Scenario 2.2, and Rp1.54 million for Scenario 2.1. These results indicate that the status quo (Scenario 1) and Scenario 2.3 were the most expensive options in terms of cost per service-level improvement.

Table 4. Service Level and Annual Inventory Cost for Each Scenario

Scenario	Service level (percent)	Yearly Inventory cost (million Rupiah)	Scenario	Service level (percent)	Yearly Inventory cost (million Rupiah)
Scenario 1			*Scenario 2.2*		
Min	18.53	17.05	Min	86.02	163.06
Mean	83.79	151.12	Mean	99.17	163.56
Max	100.00	367.75	Max	100.00	164.57
Standard deviation	22.52	66.52	Standard deviation	1.71	0.28
Scenario 2.1			*Scenario 2.3*		
Min	80.38	145.42	Min	94.70	178.58
Mean	94.80	145.65	Mean	99.90	179.35
Max	100.00	146.43	Max	100.00	180.57
Standard deviation	3.62	0.15	Standard deviation	0.49	0.33

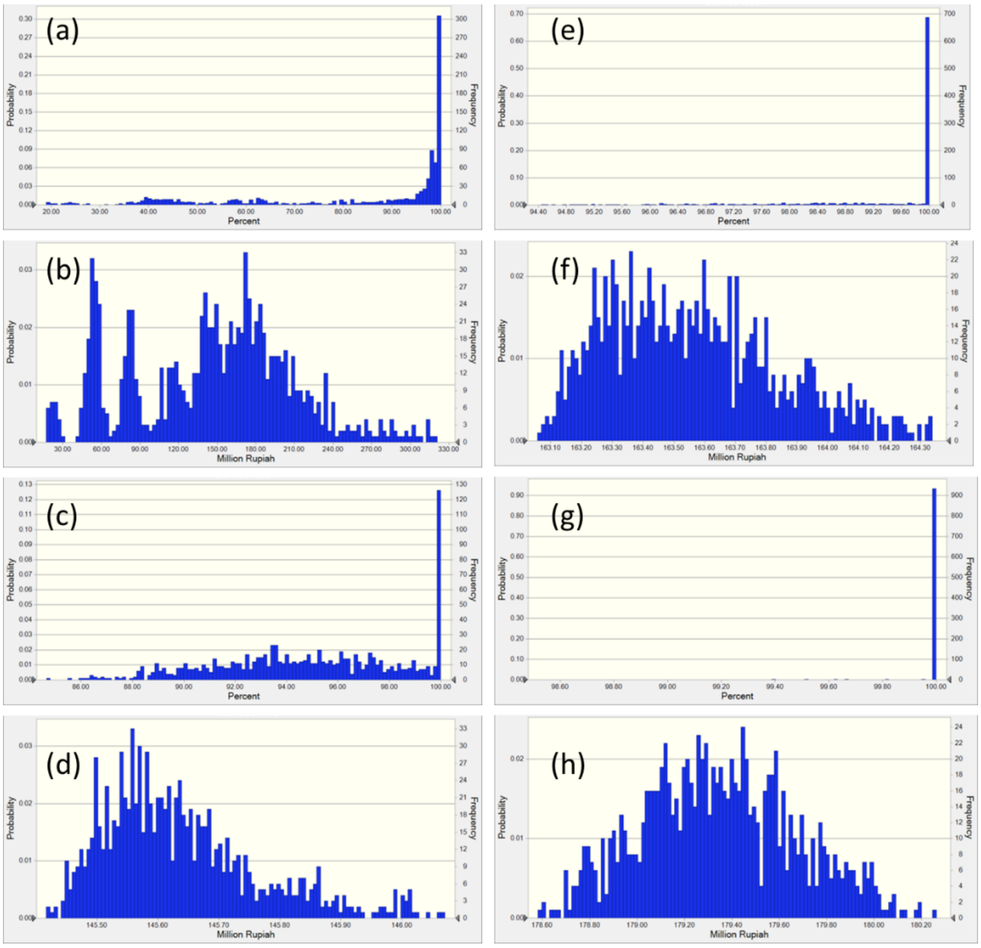

Figure 5. Service Level and Annual Inventory Cost Histograms for Each Scenario: (a) Scenario 1 Service Level, (b) Scenario 1 Annual Inventory Cost, (c) Scenario 2.1 Service Level, (d) Scenario 2.1 Annual Inventory Cost, (e) Scenario 2.2 Service Level, (f) Scenario 2.2 Annual Inventory Cost, (g) Scenario 2.3 Service Level, (h) Scenario 2.3 Annual Inventory Cost

Transitioning from status quo (Scenario 1) to Scenario 2.3 increased the service level by approximately 16% while raising the annual inventory cost by about Rp28 million. This corresponded to an additional cost of approximately Rp1.75 million per year for each 1% increase in service level. Transitioning from Scenario 1 to Scenario 2.1 and Scenario 2.2 resulted in additional costs of approximately −Rp0.50 million and Rp0.81 million per year per 1% increase in service level, respectively. These incremental costs were lower than those associated with transitioning to Scenario 2.3. Notably, transitioning from Scenario 1 to Scenario 2.1 both reduced annual inventory cost and improves service level. However, Scenario 2.3 was ultimately selected because Scenarios 2.1 and 2.2 yielded lower overall service levels. Overall, relative to the status quo (Scenario 1), shifting to Scenario 2.3 increased both service level and annual inventory cost by approximately 19%.

The methodology followed in this paper is quite similar to (Domínguez et al., 2024). The key distinction is that, in addition to cost considerations, this study introduced the maximization of service level as an objective function. Incorporating service level as an explicit objective is a defining characteristic of inventory control problems in the healthcare sector.

A similar approach was also found in (Lathifah et al., 2024). If this paper compared three scenarios combining order quantity, reorder point, annual inventory cost, and service level, Lathifah et al. (Lathifah et al., 2024) compared continuous inventory review policy (Q, R) and periodic inventory review policy (S, s). However, Lathifah et al. (Lathifah et al., 2024) focused on probabilistic demand and cost minimization, whereas the present study maximized service level while simultaneously considered inventory cost under probabilistic demand. Additional studies addressing probabilistic demand with fixed lead times can be found in Widyadana, Tanudireja, and Teng (Widyadana et al., 2017), and Sentia, Sastri, and Prasanti (Denny Sentia et al., 2018).

The results of this study are consistent with those reported by Leepaitoon and Bunterngchit (Leepaitoon & Bunterngchit, 2019). By applying ABC classification and Monte Carlo simulation to identify optimal order quantities and reorder points, both studies demonstrated the effectiveness of Monte Carlo simulation in deriving inventory policies that yield a better service level and lower inventory costs. However, while Leepaitoon and Bunterngchit (Leepaitoon & Bunterngchit, 2019) considered total inventory cost as the sole objective function, the present study adopts service level maximization as its primary objective.

The application of spreadsheet-based Monte Carlo simulation has also been reported by Lila, Nowneow, and Yimsiri (Lila et al., 2022), who considered two objective functions: cost minimization and service level maximization in the automotive sector. The justification for using Monte Carlo simulation in their study is consistent with that of the present study, namely that the demand is probabilistic and does not necessarily follow a normal distribution (Lila et al., 2022).

Accordingly, the main contribution of this study lies in its formulation of service level as a primary objective while simultaneously accounting for annual inventory cost under probabilistic demand. Most prior studies have treated demand as probabilistic but focused exclusively on total cost minimization as a single objective.

Future research may extend this approach to other consumable medical supplies managed by hospitals. Methodologically, the proposed framework may also be integrated with alternative optimization techniques, such as evolutionary algorithms (Widyadana et al., 2017), linear programming (Togo, 2008), dynamic system (Enggar et al., 2022), or artificial intelligence (Preil & Krapp, 2022), to develop more accurate and robust inventory policies.

CONCLUSION

This paper successfully proposes an improved inventory policy for handscoons at Hospital X using a spreadsheet-based Monte Carlo simulation. Four inventory scenarios were evaluated, and the paper also presents the algorithm used to implement the simulation.

The Anderson–Darling goodness-of-fit test and Least Squares parameter estimation method indicate that monthly handscoons demand follows a Weibull distribution with an estimated shape parameter $\hat{\beta}$ = 5.32 and scale parameter $\hat{\alpha}$ = 262.06. The mean monthly demand is 242 boxes. The annual demand is approximately normally distributed, with a mean of 2,899 boxes and a standard deviation of about 178 boxes.

Based on the simulation results, the recommended inventory policy uses an order quantity of 216 boxes with a 27-day interval between orders. This policy achieves a mean service level of 99.9 percent and an average annual inventory cost of Rp179.35 million. Compared to the status quo, the proposed policy increases the service level by 16 percent and achieves a 100 percent service level with a certainty of 92 percent. Moreover, the policy is expected to guarantee at least a 94.7 percent service level and has approximately the same annual cost-to-service-level ratio as the status quo, namely Rp1.80 million per one percent service level.

From a modeling perspective, future simulation studies should consider supplier capacity and operational limitations. Finally, the methodology presented in this paper can be extended to other consumable medical supplies managed by the hospital.

REFERENCES

Alnahhal, M., Aylak, B. L., Al Hazza, M., & Sakhrieh, A. (2024). Economic Order Quantity: A State-of-the-Art in the Era of Uncertain Supply Chains. *Sustainability (Switzerland)*, *16*(14), 1–19. https://doi.org/10.3390/su16145965

Balkhi, B., Alshahrani, A., & Khan, A. (2022). Just-in-time approach in healthcare inventory management: Does it really work? *Saudi Pharmaceutical Journal*, *30*(12), 1830–1835. https://doi.org/10.1016/j.jsps.2022.10.013

Bialas, C., Revanoglou, A., & Manthou, V. (2020). Improving hospital pharmacy inventory management using data segmentation. *American Journal of Health-System Pharmacy*, *77*(5), 371–377.

Chu, Y., You, F., Wassick, J. M., & Agarwal, A. (2015). Simulation-based optimization framework for multi-echelon inventory systems under uncertainty. *Computers and Chemical Engineering*, *73*, 1–16. https://doi.org/10.1016/j.compchemeng.2014.10.008

Denny Sentia, P., Elia Sastri, S., & Prasanti, N. (2018). Decision Making of Inventory System Using Monte Carlo Simulation: A Case Study. *International Journal of Conceptions on Computing and Information Technology*, *6*(1), 2017–2019.

Domínguez, J. G. C., Camacho, G. P., & Juárez, S. K. P. (2024). Inventory Control in MSMEs Using Monte Carlo Simulation. In M. M. Mota & P. Scala (Eds.), *Simulation for a Sustainable Future. EUROSIM 2023. Communications in Computer and Information Science, vol 2033*. Springer.

Enggar, M., Moch Nuruddin, & Efta Dhartikasari3. (2022). Control of Raw Materials Inventory Probabilistic Model Using Monte Carlo Simulation and Dynamic System. *Jurnal Teknovasi*, *9*(01), 37–44. https://doi.org/10.55445/jt.v9i01.36

Friday, D., Savage, D., Melnyk, S., Harrison, N., Ryan, S., & Wechtler, H. (2021). A collaborative approach to maintaining optimal inventory and mitigating stockout risks during a pandemic: capabilities for enabling health-care supply chain resilience. *Journal of Humanitarian Logistics and Supply Chain Management*, *11*(2), 248–271.

González, R. N., Ortiz, O. C., Peredo, V. J., Ramos, G. A., & Mendoza, T. R. (2023). Dental Clinic Inventory Management with Monte Carlo Simulation. *Proceedings of the International Conference on Modeling and Applied Simulation, MAS*, *2023-Septe*. https://doi.org/10.46354/i3m.2023.mas.008

Heizer, J., & Render, B. (2010). *Operations Management* (10th ed.). Pearson Education.

Homem-de-Mello, T., & Bayraksan, G. (2014). Monte Carlo sampling-based methods for stochastic optimization. In *Surveys in Operations Research and Management Science* (Vol. 19, Number 1, pp. 56–85). Elsevier Science B.V. https://doi.org/10.1016/j.sorms.2014.05.001

Khokhar, S. A. (2023). The Challenges of Inventory Management in Medical Supply Chain. *South Asian Journal of Operations and Logistics*, *2*(2), 1–18. https://doi.org/10.57044/sajol.2023.2.2.2306

Kroese, D. P., Brereton, T., Taimre, T., & Botev, Z. I. (2014). Why the Monte Carlo method is so important today. *Wiley Interdisciplinary Reviews: Computational Statistics*, *6*(6), 386–392. https://doi.org/10.1002/wics.1314

Lathifah, N., Komarudin, K., & Lestari, R. B. (2024). Analysis of inventory system for jewelry raw materials using Monte Carlo simulation. *AIP Conference Proceedings*, *3215*(1).

Leaven, L., Ahmmad, K., & Peebles, D. (2017). Inventory management applications for healthcare supply chains. *International Journal of Supply Chain Management*, *6*(3), 1–7.

Leepaitoon, S., & Bunterngchit, C. (2019). The Application of Monte Carlo Simulation for Inventory Management: a Case Study of a Retail Store. *International Journal of the Computer, the Internet and Management*, *27*(2), 76–83.

Lila, B., Nowneow, A., & Yimsiri, S. (2022). Excel Based Monte Carlo Simulation for the (Q , r) Inventory Control Model. *Engineering and Technology Horizons*, *39*(2), 103–112.

Major, L. (2019). *How to perform Monte Carlo Inventory Management Simulation in Excel*. https://www.youtube.com/watch?v=Gmr2roqELho

Preil, D., & Krapp, M. (2022). Artificial intelligence-based inventory management: a Monte Carlo tree search approach. *Annals of Operations Research*, *308*(1–2), 415–439. https://doi.org/10.1007/s10479-021-03935-2

Regulation of the Minister of Health of the Republic of Indonesia Number 72 of 2016 on Pharmaceutical Service Standards in Hospitals, Applied Microbiology and Biotechnology (2016).

Saha, E., & Ray, P. (2019a). Modelling and analysis of healthcare inventory management systems. *Opsearch*, *56*(4), 1179–1198.

Saha, E., & Ray, P. K. (2019b). Modelling and analysis of inventory management systems in healthcare: A review and reflections. *Computers and Industrial Engineering*, *137*(September), 106051. https://doi.org/10.1016/j.cie.2019.106051

Schwartz, J. D., Wang, W., & Rivera, D. E. (2006). Simulation-based optimization of process control policies for inventory management in supply chains. *Automatica*, *42*(8), 1311–1320. https://doi.org/10.1016/j.automatica.2006.03.019

Shi, L., Wei, W., Smith, A., & Abbasi, G. (2024). Implementation and evaluation of an EHR-integrated perpetual inventory system in a large tertiary hospital oncology pharmacy. *American Journal of Health-System Pharmacy*, *81*(12), 546–554.

Shourabizadeh, H., Kundakcioglu, O., Bozkir, C., Tufekci, M., & Henry, A. (2023). Healthcare inventory management in the presence of supply disruptions and a reliable secondary supplier. *Annals of Operations Research*, *331*(2), 1149–1206.

Togo, D. F. (2008). Sunset Company: Risk Analysis For Capital Budgeting Using Simulation And Binary Linear Programming. *Journal of Business Case Studies (JBCS)*, *4*(3), 43–52.

Widyadana, I. G. A., Tanudireja, A. D., & Teng, H. M. (2017). Optimal Inventory Policy for Stochastic Demand Using Monte Carlo Simulation and Evolutionary Algorithm. *International Journal of Industrial Research and Applied Engineering*, *2*(1), 8–11. https://doi.org/10.9744/jirae.2.1.8-11