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Inventory optimization of perishable items using a shelf life-based heuristic approach

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ABSTRACT

This study develops a practical inventory control model for perishable pharmaceutical products by addressing the common limitation of traditional inventory methods that often overlook product shelf life or require complex optimization procedures. The proposed model enhances practicality by integrating shelf-life considerations into the (R, nQ) heuristic approach, allowing order quantities and reorder points to be determined through a simple and easily implementable procedure. This approach is further combined with a multi-criteria ABC classification that incorporates annual demand, lead time, and unit cost, enabling more informed prioritization of inventory items. The model was applied to 243 pharmaceutical products in a health department. The results show that incorporating shelf-life constraints reduced the inventory value of items exceeding their usable period by 45% and generated an overall 2% decrease in total inventory value. These findings demonstrate the model's ability to minimize waste due to expiration while maintaining operational feasibility. By offering a straightforward and shelf-life–integrated decision rule, the model provides a more practical alternative to existing inventory methods, especially in healthcare settings with limited analytical resources.

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1. INTRODUCTION

Inventory management is essential tool for balancing supply and demand, ensuring cost-efficient storage, and enhancing an organization's overall effectiveness. It really helps companies or organizations to determine how much inventory should be stored or ordered at the right time, ensuring products remain easily accessible to customers at minimal cost [1]. Inventory control and maintenance are common challenges faced by all organizations across various economic sectors. These challenges are not exclusive to profit-oriented institutions but are also encountered by social and non-profit organizations, including healthcare facilities such as hospitals [2]. Without proper inventory management, organizations risk experiencing either overstock or stockouts. Excessive inventory can cause not only consumes significant storage space but also increases financial pressure and the probability of damage, spoilage, or loss, while insufficient inventory may interrupt production activities and limit the organization's capacity to fulfill customer needs. Therefore, effective inventory planning is crucial for organizational performance [3]. Scarcity, or a condition in which demand exceeds supply, is unavoidable in inventory systems. Therefore, effective inventory management is essential to ensure that the resulting shortages are kept to a minimum [4].

These general inventory issues become more complex when the products are perishable, since limited shelf life amplifies the impact of overstock, stockouts, and demand uncertainty. Perishable products are items with a limited shelf life, meaning they maintain their quality only for a certain period. If such items exceed their shelf life while still in storage, they become unusable and merely accumulate in the warehouse. When this occurs in healthcare settings, the impact extends far beyond operational inefficiency. Expired products represent a direct financial loss because the procurement budget has already been spent, yet the items cannot be used to support patient care. Over time, the accumulation of expired medicines can reduce budget flexibility, limit the ability of health facilities to respond to fluctuating demand, and ultimately undermine the overall efficiency of the pharmaceutical supply system. Inventory of perishable products is characterized by two main issues: obsolescence and stockouts caused by demand uncertainty [5]. In the last twenty years, sectors that depend on perishable products—like food, healthcare, and retail—have experienced growing challenges in streamlining their inventory systems due to frequent supply chain disruptions and fluctuating demand . One example of a perishable product is medicine, which has a defined shelf life and often fluctuating demand. Medicines play a vital role in patient care globally. According to the World Health Organization (WHO), medicines are essential health products that should always be available in adequate quantities at health facilities and be affordable for the population [6].

There are many studies on inventory management, and not all of them considering product shelf life. K. Sigha e al. [7] conducted research that developed a new mathematical expression that considering backlog and lost sales. Donselaar e al. [8] conducted a research tusing a periodic review multi-item inventory system with exogenous lot-sizes and backordering. This research uses heuristic method, which is similar to the approach applied in this research. Wan et al. [9] examines a periodic-review inventory system with two stochastic Poisson demand classes, positive lead time, and full backorders which combined with a threshold rationing policy. Song et al. [10] examined periodic-review stochastic inventory problems that involve both fixed ordering costs and random yield. This research places greater emphasis on random yield, where the quantity received may be less than the quantity ordered due to factors such as product defects and other uncertainties. Giat et al. [11] examines the spares allocation problem in a multi-location inventory system with stochastic lead times under a periodic review policy. The system's performance is measured using the window fill rate, the probability that a customer is served within a specified time window.

Other studies have adopted linear programming-based approaches, which are often difficult to implement in real-world settings. Noble et al. [12], Suarez et al. [13], and Zwaida et al. [14] used mathematical models based on Mixed Integer Linear Programming (MILP) to manage perishable inventory. Ahmadi et al. [15] utilized Stochastic Mixed Integer Programming (SMIP) and Intelligent Inventory Management (IIM) to control pharmaceutical inventory. Sohrabi et al. [16] modeled inventory control for processed corneal tissue (PCT) using a Multi-Objective Mixed Integer Linear Programming (MOMILP) approach combined with goal programming. Greene et al. [17] developed an order planning optimization model for health commodities using linear programming, and Franco et al. [18] conducted research on pharmaceutical logistics in hospitals using mixed-integer programming models. Other studies have used a dynamic programming approach. Gharbi et al. [19] proposes an optimal control policy for unreliable manufacturing systems that produce perishable items with limited and random shelf lives in a stochastic environment. The authors formulate a stochastic dynamic programming model and solve the optimality conditions numerically to identify the parameterized structure of the optimal policy. The policy parameters are then optimized through a simulation-based approach. This research has high computational complexity, which poses a barrier to implementation in settings with limited computational capabilities.

Beyond linear programming, other researchers have explored nonlinear programming methods. Khalifa et al. [20] analyzed inventory control for perishable products using (T, S) and (s, S) policies via analytical methods based on Markov chains and regenerative process theory, aiming to minimize long-term stock state probabilities upon order arrivals. Determining the optimal order quantity (Q) in this study was complex due to the involvement of Markov analysis and regenerative processes. Macias-Lopez et al [21] developed a differential equation-based mathematical inventory model for perishable goods, incorporating complex components such as the Hessian matrix. Soni et al. [22] proposed a periodic inventory model that accounts for lead time and backorder levels under mixed uncertainty (fuzzy-stochastic). Determining the optimal Q involved mathematical cost function optimization, followed by a defuzzification process to make optimal decisions under uncertainty. Tao et al. [23] introduced a periodic review inventory model with an (S, e) ordering policy, solved using simulation-based optimization combined with Infinitesimal Perturbation Analysis (IPA) to estimate the objective function gradient. Transchel [24] discusses supply planning and inventory control for perishable products with limited shelf life, taking into account lead-time uncertainty and service level constraints. This model analyzes two scenarios: constant lead time and stochastic lead time, where demand under stochastic lead time is assumed to follow a Bernoulli distribution. This study does not consider ABC classification in determining the fill rate.

From the literature review, it indicates that most existing models are mathematically complex or overlook key considerations such as product shelf life, making them difficult to apply in practice. Many of the existing models rely on complex mathematical formulations, such as nonlinear optimization, stochastic programming, or simulation-based approaches that require detailed data input and advanced computational tools. These methods is difficult to apply because it requires specialized expertise to operate, making them difficult for healthcare facilities with limited analytical resources to adopt. Only limited research proposes simpler, implementation-friendly methods, and none combine a heuristic approach with explicit shelf-life constraints. To bridge this gap, this study develops a practical heuristic model that incorporates product shelf life that aims to be easily applicable and can be implemented using basic spreadsheet tools. The expected contribution of this study is to deliver a more practical and easily implementable method that reduces the amount of expired products, enabling facilities to optimize ordering decisions, and improving the overall efficiency of pharmaceutical stock management.

2. MODEL FORMULATION

The proposed model will be developed based on the studies by Zhang et al [25] and Axsaeter [26], and further integrated with the approach introduced by Muriana [27].

2.1. Notation & Assumption

Notations:

c_i	: Unit cost for item i
F	: Urder frequency
$G(x)$	: Loss function
$H(x)$	: Integral from G(x)
k	: Safety factor
K	: Fixed cost
L	: Replenishment leadtime
LB	: Lower bound
N	: Number of items
Q_i	: Order quantity of item i
R_i	: Reorder point item i
S	: Fill rate
SL	: Shelf life
Tc	: Cycle time
μ_i	: Average demand per year
$\theta_i = \mu_i'$	: Expected leadtime demand for item i
σ_i	: Standard deviation demand for item i
σ_i'	: Standard deviation leadtime demand for item i
$\beta_i(v)$	: Time-weighted backorders arising from lead time demand in excess of v
$\alpha_i(v)$	: Expected lead time demand in excess of v
$A_i(R_i, Q_i)$	: Probability of stockout for item i
$B_i(R_i, Q_i)$	: Expected number of backorders for item i at any time
$\varphi(k)$	: Probability Density Function (PDF) normal standard
$\Phi(x)$	: Cumulative Distribution Function (CDF) normal standard

Assumptions
1. The demand is assumed to follow a normal distribution.
2. Demand occurs one at a time for all part numbers.

These assumptions are necessary to simplify model formulation and ensure analytical tractability, but they also influence how well the results can be generalized to real-world situations. Pharmaceutical demand does not always follow a normal distribution and may exhibit sporadic or highly variable patterns. Furthermore, the assumption that demand occurs one unit at a time simplifies the representation of demand flow in the system. Even so, these assumptions are widely used in inventory theory and still offer a reasonable approximation in many healthcare settings where demand tends to stabilize over longer observation periods.

2.2. Mathematical Model

2.2.1. Modeling for Heuristic (R, nQ) Method

The objective of this model is to manage stock and replenish inventory while minimizing inventory investment. The inventory problem is formulated as follows:

Minimize inventory investment
Subject to average order frequency ≤ F
average service level ≤ S

where F and S represent the target order frequency and the target service level, respectively, as determined by the user. The expected on-hand inventory (EOI) for item i at a given time can be modeled as follows:

$$\text{EOI} = \frac{Q_i}{2} + 0{,}5 + R_i - \theta_i + B_i(R_i, Q_i) = \frac{Q_i}{2} + 0{,}5 + R_i - \theta_i + \frac{1}{Q_i}[\beta_i(R_i) - \beta_i(R_i + Q_i)] \quad (1)$$

In accordance with Axsaeter [26], the equation for EOI can be formulated as follows:

$$\text{EOI} = \frac{Q_i}{2} + 0{,}5 + R_i - \mu_i' + \frac{{\sigma'_i}^2}{Q_i}[H(k) - H(k + Q_i)] \quad (2)$$

In Eq. (2), the value 0.5 can be omitted as it does not produce a significant difference. Furthermore, the term $H(k + Q_i)$ in Eq. (2) can be disregarded since its value is often negligible. Thus, the revised EOI equation is as follows:

$$\text{EOI} = \frac{Q_i}{2} + R_i - \mu_i' + \frac{{\sigma_i'}^2}{Q_i}[H(k)] \quad (3)$$

where:

$$k = \frac{R_i - \mu_i'}{\sigma_i'} \quad (4)$$

$$\sigma_i' = \sigma\sqrt{L} \quad (5)$$

$$\mu' = L\mu \quad (6)$$

H(k) is the integral of the *loss function G(k)*, which represents the probability of a backorder for item i at a given time. The equation for *G(k)* is as follows:

$$G(k) = \int_k^\infty (v - k)\varphi(v)dv = \varphi(k) - k(1 - \Phi(\text{x})) \quad (7)$$

or

$$G(k) = \frac{(1 - S_2)Q}{\sigma'} \quad (8)$$

Thus, *H(x)* is obtained from the integral of *G(v),* as follows:

$$H(x) = \int_x^\infty G(v)dv = \frac{1}{2}[(x^2 + 1)\big(1 - \Phi(x)\big) - x\varphi(x)] \quad (9)$$

The order frequency per year can be formulated as follows:

$$F = \frac{\mu_i}{Q_i} \tag{10}$$

The average service level is given as follows:

$$Avr. service\ level = 1 - A_i(R_i, Q_i) = \frac{1}{Q_i}[\alpha_i(R_i) - \alpha_i(R_i + Q_i)] \tag{11}$$

where:

$$\alpha_i(v) = \sum_{u=v+1}^{\infty}(u - v)p_i(u) \tag{12}$$

As further adapted from Axsaeter [26], the average service level is redefined as the fill rate. The equation is then modified as follows:

$$1 - A_i(R_i, Q_i) = 1 - \frac{\sigma_i{}'}{Q_i}[G(k) - G(k + Q_i)] \tag{13}$$

Similar to the previous case, the value of $G(k + Q_i)$ is negligible and can therefore be disregarded. Thus, the Eq. (13) can be simplified as follows:

$$1 - A_i(R, Q_i) = 1 - \frac{\sigma_i{}'}{Q_i}[G(k)] = 1 - \frac{\sigma_i{}'}{Q_i}\left[G\left(\frac{R_i - \mu_i{}'}{\sigma_i{}'}\right)\right] \tag{14}$$

To calculate the order quantity, a modified Economic Order Quantity (EOQ) formula is used to account for constraints on order frequency. The traditional EOQ formula is as follows:

$$Q_i = \sqrt{\frac{2K\mu_i}{c_i}} \tag{15}$$

for $K > 0$, the ordering frequency constraint is given as follows:

$$\frac{1}{N}\sum_{i=1}^{N}\frac{\mu_i}{Q_i} = \frac{1}{N}\sum_{i=1}^{N}\frac{\mu_i}{\sqrt{\frac{2K\mu_i}{c_i}}} = \frac{1}{N}\sum_{i=1}^{N}\sqrt{\frac{\mu_i c_i}{2K}} \le F \tag{16}$$

therefore,

$$K \ge \frac{1}{2}\left(\frac{1}{NF}\sum_{i=1}^{N}\sqrt{\mu_i c_i}\right)^2 \tag{17}$$

if it is defined as follows:

$$Q_i = \frac{1}{NF}\left(\sum_{i=1}^{N}\sqrt{\mu_i c_i}\right)\sqrt{\frac{\mu_i}{c_i}},\ \frac{1}{N}\sum_{i=1}^{N}\frac{\mu_i}{Q_i} = F \tag{18}$$

since $Q_i > 1$, the formula for Q_i is derived as follows:

$$Q = max\left\{\frac{1}{NF}\left(\sum_{i=1}^{N}\sqrt{c_i\mu_i}\right)\sqrt{\frac{\mu_i}{c_i}}, 1\right\} \tag{19}$$

To calculate *reorder point*, the following formula can be used:

$$R = \mu' + k\sigma' \tag{20}$$

where k is the *safety factor* which can be calculated using the following formula:

$$k = \frac{a_0 + a_1 z + a_2 z^2 + a_3 z^3}{b_0 + b_1 z + b_2 z^2 + b_3 z^3 + b_4 z^4} \tag{21}$$

with

$$z = \sqrt{ln\left(\frac{25}{g^2}\right)} \tag{22}$$

and the values of the other parameters are as follows:

$a_0 = -5.3925569$ | $b_0 = 1$
$a_1 = 5.6211054$ | $b_1 = -0.72496485$
$a_2 = -3.8836830$ | $b_2 = 0.507326622$
$a_3 = 1.0897299$ | $b_3 = 0.0669136868$
| $b_4 = -0.00329129114$

The value of g is obtained from $G(k)$ ($G(k) = g$).

Based on the initial inventory problem formulation described earlier, the model can be derived as follows:

$$Min \sum_{i=1}^{N} c_i \left\{ \frac{Q_i}{2} + R_i - \mu_i' + \frac{\sigma_i'^2}{Q_i}\left[H\left(\frac{R_i - \mu_i'}{\sigma_i'}\right)\right]\right\} \tag{23}$$

subject to:

$$Q = max\left\{\frac{1}{NF}\left(\sum_{i=1}^{N}\sqrt{c_i\mu_i}\right)\sqrt{\frac{\mu_i}{c_i}}\ ,1\right\} \tag{24}$$

$$\sum_{i=1}^{N}\frac{\mu_i}{\mu_{tot}}\left\{1 - \frac{\sigma_i'}{Q_i}\left[G\left(\frac{R_i - \mu_i'}{\sigma_i'}\right)\right]\right\} \geq S \tag{25}$$

$$\frac{1}{N}\sum_{i=1}^{N}\frac{\mu_i}{Q_i} \leq F \tag{26}$$

$$R_i \geq R(LB)_i \tag{27}$$

$$i = 1, 2, \dots, \mathrm{n} \tag{28}$$

2.2.2. Item Classification using the ABC Classification Method

The ABC classification used in this study does not rely on unit cost or annual cost, as in the traditional ABC method. Instead, items are classified by considering multiple factors and can produce different prioritization. For example, a medicine with low unit cost but long lead time and high demand would likely be classified as a high-priority item in this approach, whereas the traditional ABC would categorize it as low value. This demonstrates how the multi-criteria method captures supply risk more effectively than cost-based ranking alone. Items with a greater impact on performance are assigned a higher service level priority. The formula is as follows:

$$Index = \frac{\mu_i}{L_i {c_i}^2} \tag{29}$$

This ratio takes into account three key factors:

1. Annual demand (μ_i). Items with high demand are more critical for stock availability.
2. *Lead time* (l_i). Items with longer lead times are at greater risk of stockouts and should be given higher priority.
3. Unit cost (c_i). Items with higher unit costs require more careful management to avoid excessive inventory investment

The ABC classification procedure is as follows:

1. Calculate the index value for each item using Eq. (29)

2. Sort the items based on the index ratio (from lowest to highest)
3. Divide the items into categories A, B, and C. These categories are defined as follows
   a. Category A, consists of items with the lowest 20% index values. These items do not require prioritization and can be assigned a low service level.
   b. Category B, includes items with the middle 30% of index values. These items require a moderate service level.
   c. Category C, comprises items with the highest 50% of index values. These items carry higher risk and therefore should be assigned a higher service level.

2.2.3. Q Model Incorporating Product Shelf Life

The Q model that incorporates product shelf life is adapted from Muriana [27]. In Muriana [27], the value of Q is obtained through an iterative process to determine the optimal values of t_1 dan TC optimal. The iteration stops when the values of t_1 and TC in iteration i+1 are equal to those in iteration i; the resulting values of t_1 and TC are then used as inputs to compute the optimal Q. However, in this study, the value of Q is obtained in advance, and the analysis focuses on whether the resulting Q exceeds the product's shelf life. If it does, Q must be adjusted to ensure that the quantity is optimal and the inventory is depleted before the product expires. The inventory graph is illustrated in Figure 1 and Figure 2 below.

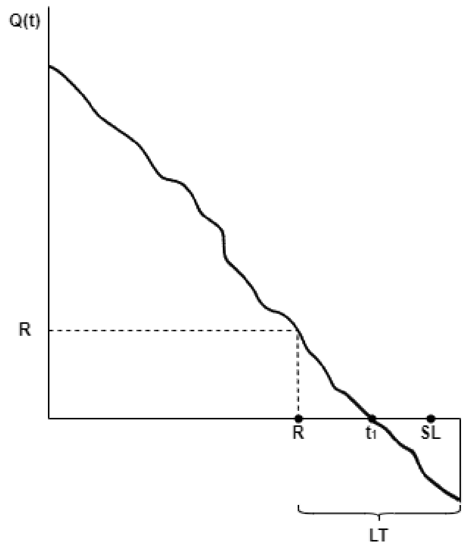

Figure 1. Inventory graph and the relationship between t_1 dan SL ($t_1 \leq SL$)

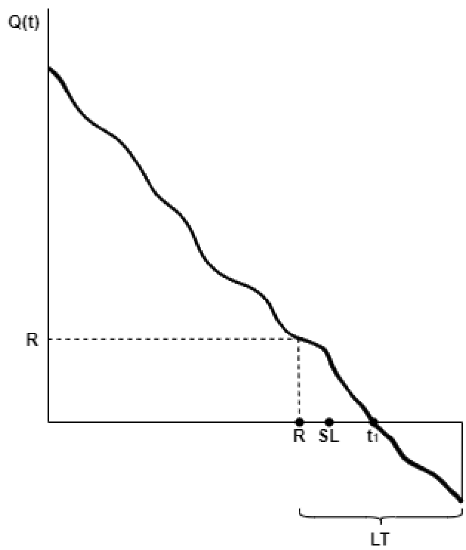

Figure 2. Inventory graph and the relationship between t_1 dan SL ($t_1 > SL$)

The explanation for Figure 1 and Figure 2 are as follows:

1) $t_1 \le SL$. In this case, the inventory is depleted before the end of the product's shelf life, so no items expire. The stockout quantity corresponds to the unmet demand occurring between t_1 and order arrival.
2) $t_1 > SL$. In this case, the remaining items between t_1 and SL have already expired and can no longer be sold. The stockout quantity equals the unmet demand between t_1 and order arrival, plus the number of expired items between SL and t_1.

Through this adjustment, the model ensures that ordered quantities are realistically consumable within the remaining shelf life, which in practice prevents overstocking and helps suppress the accumulation of expired stock. As a result, the model helps minimize waste and improves inventory efficiency in real operational settings.

Based on the explanation above, the Expected Inventory On Hand (EIH) can be calculated as follows:

$$EIH = \int_0^{t_1} Q(t)dt = \int_0^{t_1} r_t(t_1 - t)dt = r_t \frac{{t_1}^2}{2} \tag{30}$$

where

$$t_1 = \frac{Q}{r_t} = \frac{Q}{\mu + k\sigma} \tag{31}$$

where k is a *safety factor* that can be calculated using Eq. (21).

The number of expired items is given by:

$$EO = \left(Q(0) - \int_0^{SL} r_t\, dt\right) P(t_1 > SL) = r_t(t_1 - SL)P(t_1 > SL) \tag{32}$$

where $P(t_1 > SL)$ is the probability that inventory remains after the product's shelf life has ended. The t_1 represents the time at which the inventory is depleted and is assumed to follow a normal distribution with a mean of μ_{t_1} dan standard deviation of σ_{t_1}, defined as follows:

$$\mu_{t_1} = \frac{Q}{r_t} \tag{33}$$

$$\sigma_{t_1} = \frac{\sigma_t}{\sqrt{r_t}} \tag{34}$$

Calculate the Z-score for the shelf life (SL) on the standard normal distribution scale, as follows:

$$Z = \frac{SL - \mu_{t_1}}{\sigma_{t_1}} \tag{35}$$

After obtaining the Z-score, determine the cumulative probability using the standard normal Z-table

$$P(t_1 \le SL) = P(Z) \tag{36}$$

$$P(t_1 > SL) = 1 - P(t_1 \le SL) \tag{37}$$

2.3. Model Solution

The procedure for implementing the developed model is as follows:

1. Determine the target order frequency and target fill rate for each ABC classification group, where $S_A \le S_B \le S_C$.
2. Calculate the expected leadtime demand (μ′) using Eq. (6), the demand standard deviation (σ_i), and the lead time demand standard deviation ($\sigma_i{}'$) using Eq. (5).
3. Calculate the order quantity using Eq. (19).
4. Calculate the order frequency using Eq. (10).
5. Compute the index value for each item to determine the item grouping in the ABC classification using Eq. (29).
6. Sort items based on their index values in ascending order, then assign target service levels as follows: the first 20% of items are classified as Category A (S_A), the next 30% as Category B (S_B), and the final 50% as Category C (S_C).

7. Determine the lower bound of R, which in this case is equal to the expected lead time demand.
8. Calculate G(k) using Eq. (8) and the value of z using Eq. (22).
9. Calculate the safety factor k using Eq. (21).
10. Calculate the reorder point R using Eq. (20).
11. Calculate the value of k (k-adjusted) using Eq. (4).
12. Recalculate the value of G(k) using Eq. (7).
13. Calculate the fill rate by rearranging Eq. (7), as follows:

$$S_2 = 1 - \frac{\sigma' G(k)}{Q} \tag{38}$$

14. Calculate H(x) using Eq. (9).
15. Calculate the inventory values using Eq. (23).
16. Calculate the value of t_1 to assess whether the inventory plan exceeds the product's shelf life. t_1 is calculated using Eq. (31)
17. Check the values of t_1 and shelf life (SL). If t_1 > SL, then Q needs to be recalculated, but if $t_1 \leq$ SL, no recalculation is needed.
18. If t_1 > SL, determine the time difference (t_{1s}), and the corresponding quantity difference (Q_s) as follows:

$$t_{1s} = t_i - SL \tag{39}$$

$$Q_s = t_{1s} \times (\mu + k\sigma) \tag{40}$$

19. Calculate the Q optimal (Q_{opt}) using the following formula:

$$Q_{opt} = Q + Q_s \tag{41}$$

20. Repeat steps 4 through 15 using the new input Q_{opt}.

To provide a clearer overview of the model implementation, the following flow diagram summarizes the main steps of the solution procedure. The diagram is presented Figure 3 in below.

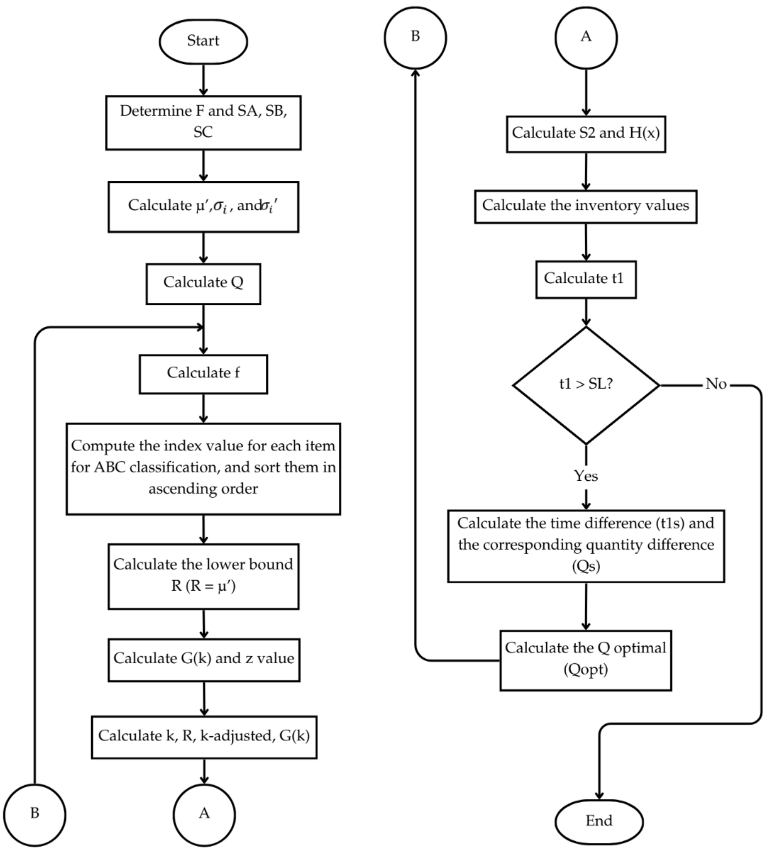

Figure 3. The flow diagram of the model solution procedure

3. RESULTS

This model will be applied to a case study at a local health department, which serves as a distribution center for supplying medicines to community health centers within a specific region. The model is implemented on 243 medicine items. This is the total number of medicines included in the case study. The dataset of 243 items is a strong representation of real operational conditions because it includes medicines with highly varying characteristics, ranging from fast-moving to slow-moving items, short to long lead times, and low to high unit costs. Such variability makes it suitable for testing whether the proposed model can accommodate heterogeneous inventory behaviors. By setting a target ordering frequency of six times per year (F = 6) and S_A = 0.6, S_B = 0.85, dan S_C = 0.99, the results are obtained as shown in Table 1.

Table 1. Inventory control calculation for 243 items of medicines

No	Item	Unit Cost (IDR)	Leadtime	Annual Demand	Q	Order Frequency	R	Inventory values (IDR)
1	Reagen Trucal L	4,573,200.00	0.1083	12	2	6	2	8,024,685.29
2	Control BC-3D	1,300,000.00	0.7472	7	3	3	6	2,961,107.43
3	Reagen HDL-c direct FS	4,314,570.00	0.1083	30	4	8	4	12,123,681.96
4	Reagen Trulab N	2,175,600.00	0.1083	25	4	7	3	5,610,849.17
5	Reagen Trucal U	1,498,500.00	0.1083	20	5	4	3	5,117,588.80
								....
240	Amlodipine 5 mg	58.83	0.2472	1,387,600	180,532	8	350,443	5,748,953.42
241	Cetrizine tab 10 mg	74.00	0.0805	716,900	115,700	7	59,000	4,375,186.66
242	Calcium Lactate tab. 500 mg	79.20	0.0805	830,600	120,380	7	68,895	4,926,541.25
243	Combined Iron Supplement Tablets	205.00	0.0027	2,557,250	131,290	20	7,217	13,484,841.12

Next, it is necessary to determine whether the obtained Q values are appropriate and do not exceed the product shelf life. After calculating t_1 and comparing it with the shelf life of each item, it was found that 15 pharmaceutical items exceeded their respective shelf lifes. The 15 items account for around 6.2% of all 243 items analyzed, suggesting that while the majority of products comply with their shelf-life constraints, a non-negligible subset may lead to overstock and potential expiration if not adjusted. The results for these 15 items are presented in Table 2 below.

Table 2. Result for 15 exceeding product shelf life

No	Item	Unit Cost (IDR)	Leadtime (year)	Annual Demand	SL (days)	t_1 (days)	$t_1 \leq$ SL?
1	Control BC-3D	1,300,000.00	0.7472	7	80	136.8	No
2	Abacavir/Lamivudine 120mg/60mg	71,670.00	0.0027	37	55	180	No
3	Aminophylline inj. 24 mg/ml-10 ml.	7,770.00	0.1083	80	139	532.8	No

No	Item	Unit Cost (IDR)	Leadtime (year)	Annual Demand	SL (days)	t_1 (days)	$t_1 \leq$ SL?
4	Magnesium sulfate inj. 20%	4,972.80	0.0805	45	532	871.2	No
5	Magnesium sulfate inj. 40%	5,659.47	0.0027	32	422	651.6	No
6	Atropine Sulfate inj. 0.25mg/ml	1,718.00	0.1222	140	86	849.6	No
7	Phenobarbital inj. mg/ml 2 ml	3,887.00	0.0027	30	707	788.4	No
8	Furosemide inj. 10 mg	00.00	0.0027	163	136	637.2	No
9	Methylergometrine M. inj. 0,200 mg.	2,050.00	0.0027	122	453	766.8	No
10	Diazepam inj. 5 mg/ml - 2 ml	1,545.00	0.0027	193	606	741.6	No
11	Contrimoxazole suspension	2,119.00	0.0027	889	289	306	No
12	Oxytocin injection 10 IU/ml-1 ml.	3,200.00	0.0027	3048	49	136.8	No
13	Diethylcarbamazine citrate 100 mg.	413.00	0.0027	550	207	874.8	No
14	Primaquine 15 mg.	360.00	0.0027	900	276	734.4	No
15	Multivitamin - Ascorbic Acid/Vit. C 500 mg	42.75	0.0027	4700	666	939.6	No

The pharmaceutical items that exceeded their shelf life were recalculated through several iterations to determine an optimal order quantity (Q) that does not exceed the product's shelf life. In this case, three iterations were conducted. The results are presented in Table 3 below.

Table 3. Result after several iterations

No	Item	Q optimal	Order Frequency	R	Inventory Values (IDR)	SL (year)	t_1 (year)	$t_1 \leq$ SL?
1	Control BC-3D	1.74	5	6	2,149,636.72	0.22	0.22	Yes
2	Abacavir/Lamivudine 120mg/60mg	8.07	5	1	353,691.45	0.15	0.15	Yes
3	Aminophylline inj. 24 mg/ml-10 ml.	31.71	3	9	126,338.64	0.39	0.39	Yes
4	Magnesium sulfate inj. 20%	68.48	1	4	172,130.28	1.48	1.48	Yes
5	Magnesium sulfate inj. 40%	57.48	1	1	167,803.29	1.17	1.17	Yes
6	Atropine Sulfate inj. 0.25mg/ml	33.79	5	18	30,706.32	0.24	0.24	Yes
7	Phenobarbital inj. mg/ml 2 ml	93.08	1	1	184,477.05	1.96	1.96	Yes
8	Furosemide inj. 10 mg	65.91	3	1	80,450.74	0.38	0.38	Yes
9	Methylergometrine M. inj. 0,200 mg.	169.97	1	1	175,572.52	1.26	1.26	Yes
10	Diazepam inj. 5 mg/ml - 2 ml	339.34	1	1	262,851.54	1.68	1.68	Yes
11	Cotrimoxsazole suspension	717.05	2	3	760,839.75	0.8	0.8	Yes
12	Oxytocin injection 10 IU/ml-1 ml.	414.1	8	17	690,163.00	0.14	0.13	Yes
13	Diethylcarbamazine citrate 100 mg.	322.94	2	2	66,885.00	0.58	0.58	Yes
14	Primaquine 15 mg.	703.96	2	3	126,893.42	0.77	0.77	Yes
15	Multivitamin - Ascorbic Acid/Vit. C 500 mg	8,740.2	1	14	186,864.98	1.85	1.85	Yes

The comparison of inventory values between the model without considering product shelf life and the model that accounts for product shelf life is presented in Table 4. Based on the Table 4, it can be seen that the inventory values reduction achieved by comparing the model without considering shelf life to the model that incorporates shelf life is 45%. This 45% reduction in inventory value carries significant operational implications for healthcare facilities. Lowering the amount of capital tied up in stock means that a smaller portion of the budget needs to be allocated for purchasing and maintaining inventory, allowing funds to be redirected to other essential services or high-priority programs. In addition, the decrease in excess inventory directly reduces the likelihood of products expiring before use, which in turn minimizes waste-related expenses such as the handling, documentation, and disposal of expired medicines. Since disposal processes in healthcare settings often require specialized procedures and regulatory compliance, the associated costs can be substantial. Thus, achieving a 45% reduction not only improves budget efficiency but also leads to tangible savings in operational and administrative workloads, ultimately supporting a more sustainable inventory management system.

Table 4. The comparison of inventory values

No	Item	Inventory values without considering product shelf life (IDR)	Inventory values with considering product shelf life (IDR)
1	Control BC-3D	2,961,107.43	2,149,636.72
2	Abacavir/Lamivudine 120mg/60mg	1,032,048.02	353,691.45
3	Aminophylline inj. 24 mg/ml-10 ml.	468,917.60	126,338.64
4	Magnesium sulfate inj. 20%	280,330.00	172,130.28
5	Magnesium sulfate inj. 40%	256,996.53	167,803.29
6	Atropine Sulfate inj. 0.25mg/ml	290,168.26	30,706.32
7	Phenobarbital inj. mg/ml 2 ml	205,700.06	184,477.05
8	Furosemide inj. 10 mg	369,728.32	80,450.74
9	Methylergometrin M. inj. 0,200 mg.	295,528.16	175,572.52
10	Diazepam inj. 5 mg/ml - 2 ml	322,071.26	262,851.54
11	Contrimoxazole suspension	808,464.15	760,839.75
12	Oxytocin injection 10 IU/ml-1 ml.	1,838,728.19	690,163.00
13	Diethylcarbamazine citrate 100 mg.	280,415.51	66,885.00
14	Primaquine 15 mg.	334,800.23	126,893.42
15	Multivitamin - Ascorbic Acidt/Vit. C 500 mg	263,510.57	186,864.98
Total		10,008,514.31	5,535,304.69
%		45%	

4. DISCUSSION

The proposed model is developed based on a combination of models from Zhang et al [25] and Axsaeter [26] combine with Muriana [27]. In Zhang et al [25], the model was applied to a multi-component distribution center supplying spare parts, where the products were not categorized as perishable goods with limited shelf life. Meanwhile Axsaeter [26] developed an inventory system model assuming normally distributed demand, consisting of two systems: continuous review (R, nQ) and periodic review (T, S). So this paper modifies the models of Zhang et al [25] and Axsaeter [26] to address the inventory control of perishable goods, incorporating shelf life considerations from Muriana [27]. The modifications to the formulas are presented in the model formulation section. These modifications include eliminating terms with negligible values, such as in Eq. (3) and Eq. (14), or replacing them with specific values as in Eq. (13). Additionally, the model integrates the ABC classification method, enhanced by considering multiple factors—unlike the classical ABC approach which typically only accounts for unit cost or annual cost. The factors considered in this model include annual demand, lead time, and unit cost. These allow for a more critical classification of items, better reflecting the contribution and risk of each item within the inventory system.

Unlike most inventory control models, this model operates as an aggregate inventory control model that does not explicitly consider inventory cost components such as holding cost, ordering cost, or backorder cost, which are often inaccurately estimated or based on assumptions. For instance, companies frequently lack precise information regarding holding costs. To minimize such assumptions, this model only considers product prices while still being capable of determining inventory components optimally such as order quantities, ordering frequencies, and reorder points.

Table 1 presents the calculation results of inventory values for 243 drug items without considering the shelf life of the products. At this stage, the model solution process was only carried out from Step 1 to Step 15, without progressing to Steps 16–20. In this initial calculation, the model was applied by setting a target ordering frequency of six times per year, with fill rates for group A (S_A) of 0.60, group B (S_B) of 0.85, and group C (S_C) of 0.99. After proceeding to Steps 16–17, it was found that there were 15 drug items whose calculated order quantities (Q) exceeded the product shelf life, as shown in Table 2. These 15 items were then recalculated (corresponding to Steps 18–20 in the model solution). The recalculation process required three iterations, resulting in the final values presented in Table 3. The final inventory values for these 15 items were then compared with their corresponding values from the calculation without shelf life consideration, as shown in Table 4.

Based on the case study results presented in Table 4, the application of the developed model resulted in a 45% reduction in inventory value for the 15 items identified as exceeding their shelf life. This indicates that the Q-based method without shelf life considerations tends to generate excessively large order quantities, ultimately leading to a high number of expired medicines. The expiration of such drugs is both unfortunate and financially detrimental, as the products are rendered unusable and result in direct losses. Furthermore, using Eq. (32), all calculated values for expired items were negative, indicating that no items exceeded their shelf life after model adjustment. On a broader scale, for all items considered in the case study, the implementation of this model resulted in an overall inventory value reduction of approximately 2%, or IDR 21,629,899.36. This result demonstrates that the model provides a significant improvement in optimizing inventory for perishable goods and can be easily applied without the need for advanced technology.

Compared to the conventional Q-based model, which does not incorporate shelf-life constraints, the proposed approach offers a more practical decision-making framework. The integration of shelf life not only reduces expired items but also simplifies the decision process by directly linking order quantity adjustments with product shelf life periods. This makes the model more aligned with real operational needs, especially in healthcare settings where demand variability and limited storage capacity require straightforward and easily implementable solutions.

5. CONCLUSION

This study presents an inventory control model that integrates product shelf life considerations into a modified (R, nQ) system. Unlike traditional models, this approach omits complex cost assumptions such as holding or ordering costs and instead emphasizes product price and demand behavior. It also incorporates a multi-criteria ABC classification to improve prioritization of items based on annual demand, lead time, and unit cost. Applied to a case study involving 243 pharmaceutical items at a regional health office, the model demonstrated its practical value by reducing inventory value by 45% for 15 items that initially exceeded their shelf life, and achieving an overall inventory reduction of 2% (equivalent to IDR 21,629,899.36). These results indicate the model's effectiveness in preventing expiration-related losses and optimizing stock levels for perishable products, and it can be easily applied without the need for advanced technology .

However, this study has certain limitations. The model assumes normally distributed demand and does not incorporate stochastic lead times, dynamic pricing, or other operational constraints such as supplier capacity or budget limitations. Future research should explore extending this model to account for variable lead times, demand uncertainty beyond normal distribution, and multi-echelon supply chains. Despite these limitations, the model offers strong real-world applicability, as it can be implemented using routinely available inventory data and simple computational tools. The calculation procedures can be implemented using simple spreadsheet software, enabling rapid integration into existing inventory workflows. Given its low computational requirements and intuitive decision rules, the model can be readily adopted by other healthcare institutions or public health agencies that manage perishable items and face similar challenges related to waste reduction and stock expiration. This practical adaptability highlights the model's potential to support broader improvements in inventory management across diverse organizational settings.

REFERENCES

[1] I. M. S. Al Ruqeishi and A. Ullah, "Inventory management: methods, approaches, benefits and challenges," *International Journal of Social Sciences and Management Review*, vol. 07, no. 04, pp. 10–18, 2024, doi: 10.37602/ijssmr.2024.7402.

[2] R. J. Tersine, *Principles of Inventory and Materials Management*, 4th ed. New Jersey: Prentice-Hall, Inc, 1994.

[3] L. P. H. Shanilka and C. A. Kavirathna, "Impacts of inventory management factors on inventory performance measures: The Sri Lankan wholesale sector," *Journal of South Asian Logistics and Transport*, vol. 4, no. 2, pp. 109–147, Sep. 2024, doi: 10.4038/jsalt.v4i2.96.

[4] S. Schiffels and C. Jost, "The role of scarcity behavior in inventory management," *Eur J Oper Res*, vol. 328, no. 1, pp. 78–90, Jan. 2026, doi: 10.1016/j.ejor.2025.05.043.

[5] K. Chen, T. Xiao, S. Wang, and D. Lei, "Inventory strategies for perishable products with two-period shelf-life and lost sales," *Int J Prod Res*, vol. 59, no. 17, pp. 5301–5320, 2021, doi: 10.1080/00207543.2020.1777480.

[6] A. T. Kefale and H. H. Shebo, "Availability of essential medicines and pharmaceutical inventory management practice at health centers of Adama town, Ethiopia," *BMC Health Serv Res*, vol. 19, no. 1, Apr. 2019, doi: 10.1186/s12913-019-4087-0.

[7] K. Singha, J. Buddhakulsomsiri, and P. Parthanadee, "Mathematical Model of (R,Q) Inventory Policy under limited storage space for continuous and periodic review policies with backlog and lost sales," *Math Probl Eng*, vol. 2017, pp. 1–9, 2017, doi: 10.1155/2017/4391970.

[8] K. van Donselaar, R. Broekmeulen, and T. de Kok, "Heuristics for setting reorder levels in periodic review inventory systems with an aggregate service constraint," *Int J Prod Econ*, vol. 237, Jul. 2021, doi: 10.1016/j.ijpe.2021.108137.

[9] G. Wan and Y. Cao, "A continuous cost evaluation approach for periodic review inventory systems with threshold rationing policy," *Comput Ind Eng*, vol. 126, pp. 75–87, Dec. 2018, doi: 10.1016/j.cie.2018.09.018.

[10] Y. Song and Y. Wang, "Periodic review inventory systems with fixed order cost and uniform random yield," *Eur J Oper Res*, vol. 257, no. 1, pp. 106–117, Feb. 2017, doi: 10.1016/j.ejor.2016.07.005.

[11] Y. Giat and M. Dreyfuss, "Optimizing spares in a multiple location facility with periodic review," in *Procedia Manufacturing*, Elsevier B.V., 2019, pp. 1673–1680. doi: 10.1016/j.promfg.2020.01.273.

[12] J. Noble, K. John, and B. Paul, "Inventory management of perishable products with fixed shelf life for a single echelon system," in *Materials Today: Proceedings*, Elsevier Ltd, Jan. 2023, pp. 2863–2868. doi: 10.1016/j.matpr.2022.07.299.

[13] C. A. Suárez, W. A. Guaño, C. C. Pérez, and H. Roa-López, "Multi-objective optimization for perishable product dispatch in a FEFO system for a food bank single warehouse," *Operations Research Perspectives*, vol. 12, Jun. 2024, doi: 10.1016/j.orp.2024.100304.

[14] T. A. Zwaida, C. Pham, and Y. Beauregard, "Optimization of inventory management to prevent drug shortages in the hospital supply chain," *Applied Sciences (Switzerland)*, vol. 11, no. 6, Mar. 2021, doi: 10.3390/app11062726.

[15] E. Ahmadi, H. Mosadegh, R. Maihami, I. Ghalehkhondabi, M. Sun, and G. A. Süer, "Intelligent inventory management approaches for perishable pharmaceutical products in a healthcare supply chain," *Comput Oper Res*, vol. 147, Nov. 2022, doi: 10.1016/j.cor.2022.105968.

[16] M. Sohrabi, M. Zandieh, and B. Afshar-Nadjafi, "A simple empirical inventory model for managing the processed corneal tissue equitably in hospitals with demand differentiation," *Computational and Applied Mathematics*, vol. 40, no. 8, Dec. 2021, doi: 10.1007/s40314-021-01663-8.

[17] C. Greene, Z. B. Zabinsky, D. Sarley, and L. Akhlaghi, "Inventory and order management for healthcare commodities during a pandemic," *Ann Oper Res*, vol. 337, no. 1, pp. 105–133, Jun. 2024, doi: 10.1007/s10479-024-05870-4.

[18] C. Franco and E. Alfonso-Lizarazo, "Optimization under uncertainty of the pharmaceutical supply chain in hospitals," *Comput Chem Eng*, vol. 135, Apr. 2020, doi: 10.1016/j.compchemeng.2019.106689.

[19] A. Gharbi, J. P. Kenné, and R. Kaddachi, "Dynamic optimal control and simulation for unreliable manufacturing systems under perishable product and shelf life variability," *Int J Prod Econ*, vol. 247, May 2022, doi: 10.1016/j.ijpe.2022.108417.

[20] F. Ben Khalifa, C. Kouki, I. Safra, and Z. Jemai, "Analysis and optimisation of periodic inventory models for perishable items with a general lifetime," *Int J Prod Res*, vol. 61, no. 21, pp. 7483–7501, 2023, doi: 10.1080/00207543.2022.2150908.

[21] A. Macías-López, L. E. Cárdenas-Barrón, R. E. Peimbert-García, and B. Mandal, "An inventory model for perishable items with price-, stock-, and time-dependent demand rate considering shelf-life and nonlinear holding costs," *Math Probl Eng*, vol. 2021, 2021, doi: 10.1155/2021/6630938.

[22] H. N. Soni and M. Joshi, "A periodic review inventory model with controllable lead time and backorder rate in Fuzzy-stochastic environment," *Fuzzy Information and Engineering*, vol. 7, no. 1, pp. 101–114, Mar. 2015.

[23] Y. Tao, L. H. Lee, E. P. Chew, G. Sun, and V. Charles, "Inventory control policy for a periodic review system with expediting," *Appl Math Model*, vol. 49, pp. 375–393, Sep. 2017, doi: 10.1016/j.apm.2017.04.036.

[24] S. Transchel and O. Hansen, "Supply planning and inventory control of perishable products under lead-time uncertainty and service level constraints," in *Procedia Manufacturing*, Elsevier B.V., 2019, pp. 1666–1672. doi: 10.1016/j.promfg.2020.01.274.

[25] R. Q. Zhang, W. J. Hopp, and C. Supatgiat, "Spreadsheet implementable inventory control for a distribution center," *Journal of Heuristic*, vol. 7, pp. 185–203, 2001.

[26] S. Axsaeter, *Inventory Control* , 3rd ed. Switzerland: Springer International Publishing, 2015.

[27] C. Muriana, "An EOQ model for perishable products with fixed shelf life under stochastic demand conditions," *Eur J Oper Res*, vol. 255, no. 2, pp. 388–396, Dec. 2016, doi: 10.1016/j.ejor.2016.04.036.