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# A Genetic Algorithm for Medicine Inventory Management Under Uncertain Demand

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## Abstract:

**Objective:** This study aimed to propose an optimal drug inventory management approach for government hospitals under uncertain demand, particularly during emerging disease scenarios like Coronavirus Disease 2019 (COVID-19). The goal was to minimize inventory management costs, including holding, ordering, and drug costs, by determining the optimal order quantity and reorder point.

**Material and Methods:** Drugs were categorized using the K-Means Clustering method to identify similar demand patterns. A mathematical model and a genetic algorithm (GA) were developed to determine the optimal ordering policy. These methods were evaluated based on total inventory management costs and processing times. Sensitivity analysis was performed to evaluate the effects of cost variations, with increments ranging from 10% to 50%.

**Results:** The mathematical model achieved a total inventory management cost of 80,652,330.9 Thai Baht (THB), a 4.7% reduction (3,800,278.1 THB) compared to the genetic algorithm's 84,452,609.0 THB. However, the genetic algorithm significantly reduced processing time to 60.2 minutes, compared to 368 minutes for the mathematical model, representing an 83.6% time reduction. Compared to the current policy's cost of 93,442,791.9 THB, the mathematical model lowered costs by 13.7% (12,790,461.0 THB), while the genetic algorithm achieved a 9.6% reduction (8,990,182.9 THB).

**Conclusion:** The proposed methods effectively reduced inventory management costs and processing times compared to the existing policy. This study introduces an integrated approach that combines K-Means clustering, a mathematical model, and a genetic algorithm to efficiently manage hospital drug inventories under uncertainty, reducing both costs and processing time.

**Keywords:** drug inventory optimization, genetic algorithm, healthcare supply chain, sensitivity analysis, uncertainty demand

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## Introduction

Efficient pharmaceutical inventory management is a crucial factor in ensuring patient safety. However, hospitals worldwide, including those in Thailand, continue to face challenges in optimizing their drug inventory. An excessive drug stock leads to insufficient storage space and the expiry of medications before dispensation, resulting in significant cost wastage. Conversely, an insufficient drug supply causes drug shortages, impacting patient treatment and damaging the hospital's reputation[1-3]. Drug shortages have been an ongoing problem in healthcare systems globally[4,5]. Nevertheless, forecasting demand in healthcare systems is difficult due to uncertainties such as changes in patient conditions, variations in physician prescribing habits, patient responses to treatment, and medical emergencies, including disease outbreaks[6].

To address these issues, past research has proposed various approaches to inventory management. Popular methods include the Economic Order Quantity (EOQ) model, Reorder Point (ROP) systems, and ABC or ABC-VEN analysis for drug categorization to reduce the complexity of inventory management[7-9]. While these methods improve inventory management efficiency, most are based on the assumption that drug demand is predictable and stable. This limitation prevents these methods from adequately responding to real-world situations with uncertain demand, especially during epidemics or public health crises[10-12]. The Coronavirus Disease 2019 (COVID-19) pandemic clearly demonstrated the limitations of traditional inventory management systems when faced with rapidly changing circumstances[13]. In light of this situation, modern research has begun to apply advanced optimization techniques, such as Genetic Algorithms (GA), to solve these problems. Reports indicate that applying GA enhances the efficiency of complex medical inventory systems, reducing staff travel distance and working time by over 50%[14]. Additionally, the Non-Dominated Sorting Genetic Algorithm II (NSGA-II), a type of GA, has been effectively used to manage cold chain product supply chains, helping to reduce costs and maintain the quality of temperature-sensitive medications and medical supplies[15].

In Thailand, public hospitals are non-profit organizations responsible for providing healthcare services to the public nationwide under limited budgets. Generally, the budget allocated for drug and medical supply inventory accounts for approximately 30-40% of the hospital's total budget[16]. The provincial public hospital serving as a case study in this research faces similar problems. Managing drug inventory under uncertain demand while effectively controlling costs is an increasingly complex mission, especially following the COVID-19 pandemic, which exposed the weaknesses of traditional inventory management policies and highlighted the need for flexible and adaptable approaches. The motivation for this research stems from the limitations of traditional drug inventory management methods, which are unable to effectively cope with uncertain demand. Although GAs have been applied in medical logistics, there is still limited research integrating drug clustering techniques with GAs to manage hospital drug inventory under uncertain demand, particularly in the context of Thailand.

For these reasons, this research aimed to apply Genetic Algorithms to improve the efficiency of determining the optimal order quantity and reorder point in the case study hospital. GAs offer advantages in terms of flexibility, faster computation time, and suitability for real-world healthcare scenarios that require rapid and efficient decision-making, which can help reduce costs and increase the operational efficiency of hospitals.

## Material and Methods

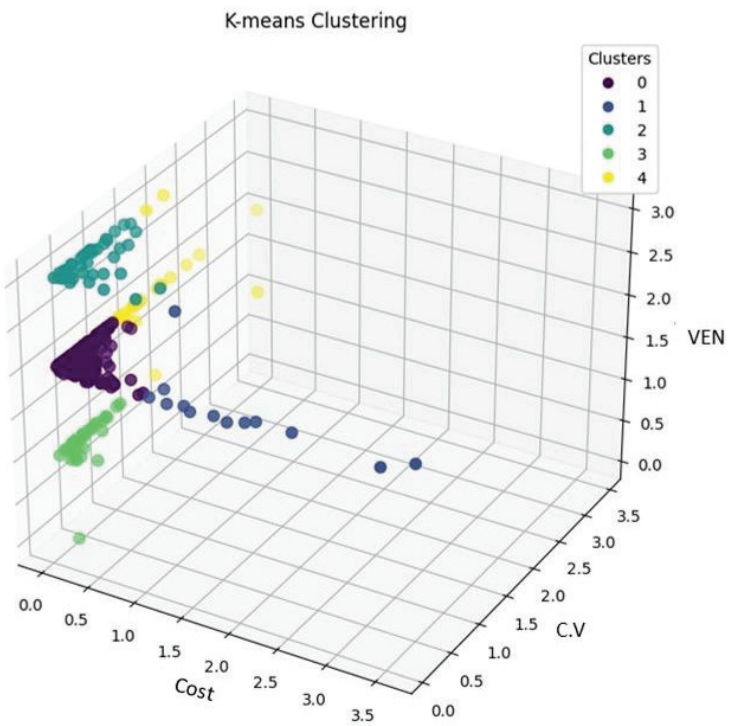
### General problem formulation and scope

The drug inventory management problem at the case study hospital involves collecting relevant data and analyzing it using mathematical models and genetic algorithms. The problem is defined under the following key assumptions: drug demand is known with certainty and is independent across items, storage costs are constant, and lead time is fixed at 30 days. Stockouts are prohibited, requiring sufficient inventory to meet all demands. The objective is to determine the optimal order quantity and reorder point to minimize total inventory costs.

**Data grouping by K-Means method**

There are 370 drug items in the inventory of the case study hospital. Historical drug demand data were collected, and demand uncertainty was analyzed to support the selection of target drug groups. Three key factors were considered in this selection process: drug value, coefficient of variation (CV), and drug importance level based on Vital, Essential, and Non-essential (VEN) analysis.

VEN analysis classifies drugs according to their clinical importance and public health impact, particularly under budget constraints. Drugs are categorized into 3 groups: Vital (V), life-saving and must always be available; Essential (E), important for treating common but serious diseases; and Non-essential (N), for minor illnesses or as alternatives. The VEN classification used in this study was based on the formal consensus of the hospital drug committee, which consisted of 3 physicians and 3 pharmacists.




CV=coefficient of variation, VEN=VEN analysis (Vital, Essential and Non-essential items)

**Figure 1** Results of drug clustering using the K-Means method

Based on the K-Means clustering results shown in Figure 1, a total of 85 drug items were selected from the 370 items in the hospital's drug inventory as the target group for further analysis and optimization of ordering and storage policies. The characteristics of each cluster are summarized as follows: Cluster 1 (blue) consists of high-cost drugs that have a significant impact on the hospital's overall inventory costs. Cluster 2 (dark green) includes drugs classified as Vital (V) according to VEN analysis and exhibits high demand variability, indicating both medical importance and supply uncertainty. Cluster 4 (yellow) also contains drugs with high demand variability and includes additional items from the Vital (V) group. These selected drugs were subsequently analyzed using a mathematical model and a Genetic Algorithm to determine the optimal order quantities and reorder points.

**Mathematical models**

In this section, a mathematical model is applied to solve the problem of drug inventory management to calculate the lowest cost of management. The objective equation is required as follows:

$$\text{Min TC} = \sum_{t=1}^{T}\left(HI_t+Sy_t+PQ^*\right) \tag{1}$$

Equation 1 represents the total cost within the drug inventory system, which consists of storage costs, ordering costs, and drug prices for all items over all periods. The goal is to minimize the total cost.

**Where:**

t = time period ; t = 1, 2, …, T (months)

TC = Total cost (baht)

$D_t$ = Drug demand in period t

M = a large value used for order decision-making

**Parameters**

H = storage cost (baht/time period)

S = ordering cost (baht/order)

$I_t$ = ending inventory at time t

$Q_t$ = quantity of drugs received in period t

L = lead time

P = drug price per unit

**Decision variables**

Q* = optimal order quantity

R = optimal reorder point

$$y_t = \begin{cases} 1 & \text{if an order is placed,} \\ 0 & \text{if no order is placed.} \end{cases}$$

These constraints are defined by equations 2 to 10, which specify the applicable conditions for the above objective function, as detailed below.

$$I_t = I_{t-1} + Q_t - D_t \tag{2}$$

Equation 2 represents the inventory level of drugs at each time period, which equals the remaining inventory from the previous period plus the quantity received in period t, minus the demand in period t.

$$I_t \geq 0 \tag{3}$$

Equation 3 ensures that the inventory level at each time period must be greater than or equal to zero, preventing stockouts in the warehouse.

$$Q^* - Q_t \leq M(1 - y_{t-L}) \tag{4}$$

Equation 4: This condition states that the quantity of drugs received in any period t depends on whether an order was placed in period t–L. If no order was placed, the value of y is 0, which means the right-hand side of the equation will equal the predefined value M, and the quantity received in period t will be 0, as no order was placed.

$$Q_t \leq My_{t-L} \tag{5}$$

Equation 5: This condition states that the quantity of drugs received in any period t depends on whether an order was placed in period t–L. If no order was placed, the value of y is 0, making the right-hand side of the equation 0. Thus, the quantity of drugs received in period t is also 0, meaning no drugs are received.

$$Q_t \leq Q^* \tag{6}$$

Equation 6: The quantity of drugs received in period t must be less than or equal to the optimal order quantity.

$$Q_t \geq 0 \tag{7}$$

Equation 7: The quantity of drugs received in period t must be greater than or equal to 0. It is expressed as Equation 7.

$$I_t - R \leq M(1 - y_t) \tag{8}$$

Equation 8: This condition governs the decision to place an order. If the final inventory at the end of period t is less than the optimal reorder point, an order will be placed.

$$R - I_t \leq My_t \tag{9}$$

Equation 9: This condition governs the decision to place an order. If no order is placed (yt =0), the right-hand side of the equation becomes 0. As a result, the final inventory at the end of the period is greater than the reorder point, making the left-hand side negative, which satisfies the condition that the left-hand side must be less than 0 when no order is placed.

$$R \geq 0 \tag{10}$$

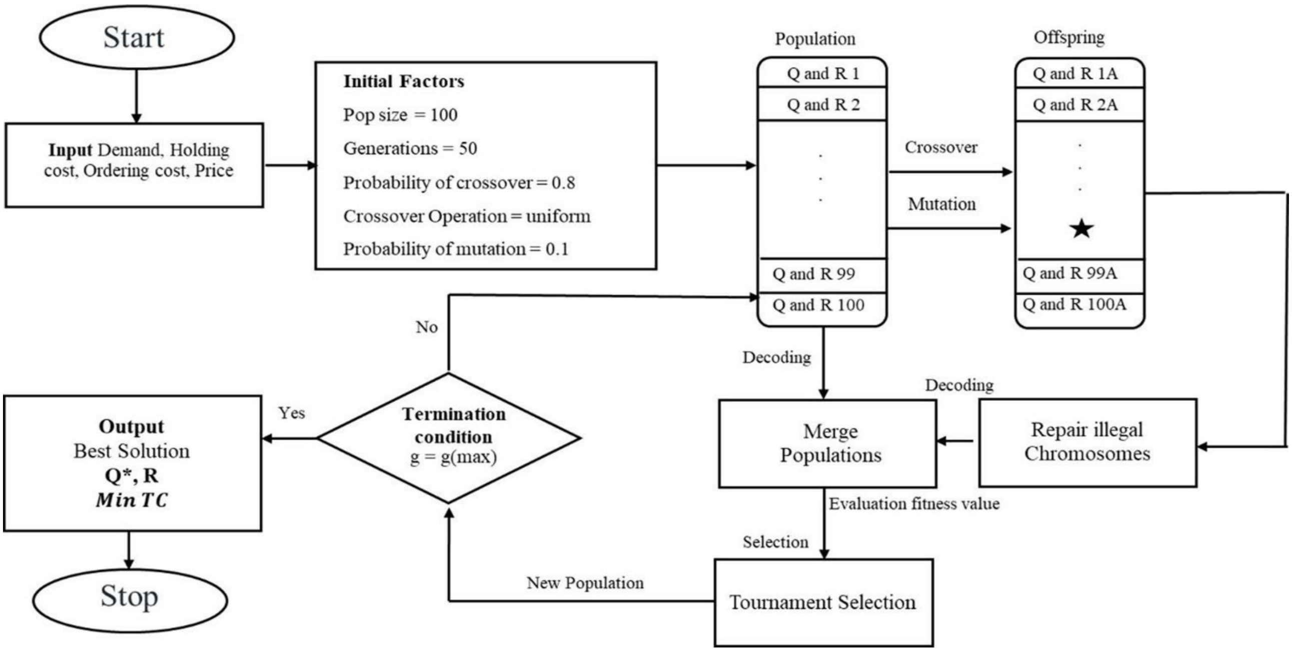
Equation 10: This condition governs the decision to place an order, ensuring that the optimal reorder point is greater than or equal to 0.

**Genetic algorithm**

This section presents the Genetic Algorithm for determining the appropriate order quantity and order point of the hospital's drug inventory. The results can be used to decide on the order of drugs that have been grouped into drug data using the K-Means method. The genetic algorithm will model a set of answers for the appropriate order quantity and order point and continuously improve these answers through a process inspired by natural selection, which is based on the theory of evolution by Charles Darwin. It is a selection of good strains as a model for passing on genetic characteristics to the next strain in order to make it a better strain and survive, which was invented by John Holland. The working process of this algorithm can be seen in Figure 2. These processes will continue for several generations, and the answers in each generation will develop into new answers with lower costs until the most suitable results are obtained, which are the set of appropriate order quantities and order points, which can help the hospital reduce the cost of managing drug inventory.

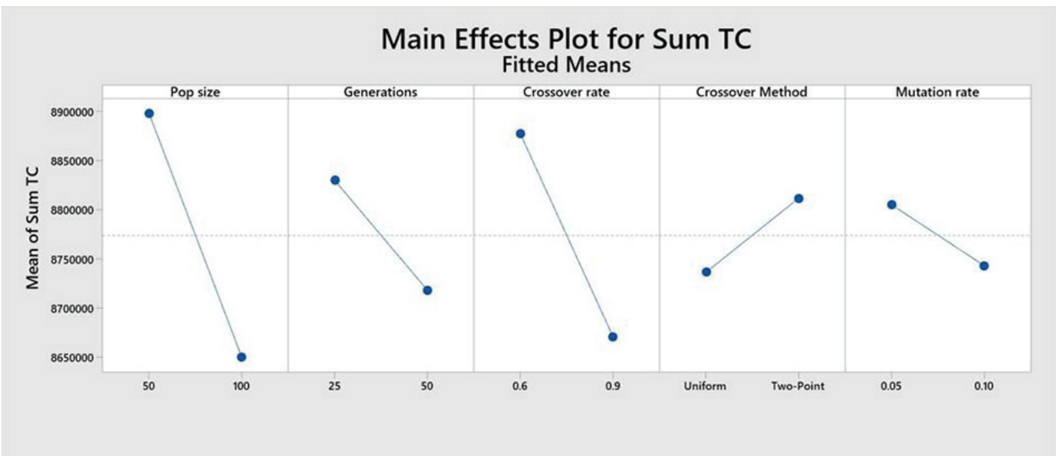
In the analysis using a Genetic Algorithm, 5 key parameters were considered, each with 2 levels: population size (50, 100), number of generations (25, 50), crossover probability (0.6, 0.9), crossover method (Uniform, Two-Point), and mutation probability (0.05, 0.1). A $2^k$ factorial design of experiment was applied to investigate the effects of these parameters on the performance of the algorithm.

From Figure 3, the factors that result in the lowest total cost are identified. The optimal factor levels are as follows: a population size of 100, generations of 50, a crossover probability of 0.9 using the uniform crossover method, and a mutation probability of 0.1.




g=generations, Q*=optimal order quantity, R=optimal reorder point, Min TC=minimize the total cost

**Figure 2** Genetic algorithmic approach for the problem




Sum TC=summation total costs

**Figure 3** Factors affecting cost

## Results

**Comparison between the genetic algorithm and mathematical model**

The comparison between the analysis results of the mathematical model and the genetic algorithm (GA) for a dataset of 85 items is shown in Table 1.

From a cost perspective, the mathematical model performed better in reducing hospital drug inventory costs due to its ability to simulate scenarios and achieve the most probable outcome (Global Optimal Solution). The mathematical model resulted in a total inventory management cost of 80,652,330.9 THB, which was the lowest cost. In contrast, the GA produced results that were not the absolute best but rather a set of solutions (Local Optimal Solution). Consequently, the GA had a higher cost, with a total inventory management cost of 84,452,609.0 THB for the same dataset. This cost was 3,800,278.0 THB or 4.7% higher than the mathematical model. However, when considering processing time, the mathematical model required 368 minutes to complete the calculations. For the same dataset, the GA only required 60.2 minutes to calculate the reorder points and storage quantities, which was 308.8 minutes faster or 83.6% quicker than the mathematical model.

The analysis of processing time showed that the genetic algorithm could adapt to complex and large-scale problems without requiring restrictive conditions that limit the feasibility of optimal solutions. In contrast, the mathematical model required more time to obtain results, as it needed to evaluate all possible solutions.

**Comparison of the mathematical model and genetic algorithm with the hospital's existing procurement policy**

When analyzing the hospital's existing procurement policy using a dataset of 85 samples and simulating the same drug dispensing scenario, the results reveal differences in inventory management costs. The hospital's existing procurement policy incurs a total cost of 93,442,791.9 THB. In contrast, the mathematical model resulted in a total inventory management cost of 80,652,330.9 THB, reflecting a cost reduction of 12,790,461.0 THB, or approximately 13.7%. Meanwhile, the genetic algorithm achieved a total cost of 84,452,609.0 THB, reducing costs by 8,990,182.9 THB compared to the hospital's existing policy, which represents a cost reduction of approximately 9.6%. The comparison is illustrated in Figure 4.

**Sensitivity analysis**

The analysis of the sensitivity of hospital costs, including storage costs, ordering costs, and drug costs, is crucial for resource management. It affects the efficiency of service delivery and the hospital's finances. Analyzing the sensitivity of these costs helps hospital administrators understand how to adapt correctly in various situations. It enables them to analyze adjustments to economic

**Table 1** Comparison between the genetic algorithm and mathematical model

| Number of items | Total cost (THB) | | Processing time (minutes) | |
|---|---|---|---|---|
| | GA | Math model | GA | Math model |
| 85 | 84,452,609.0 | 80,652,330.9 | 60.2 | 368 |

GA=genetic algorithm, Math model=mathematical model, THB=Thai Baht conditions, changes in the hospital's cost structure, or adjust drug inventory management policies accordingly. Therefore, the researchers analyzed the sensitivity to changes in order to see the impact of these costs on the hospital's total cost value.

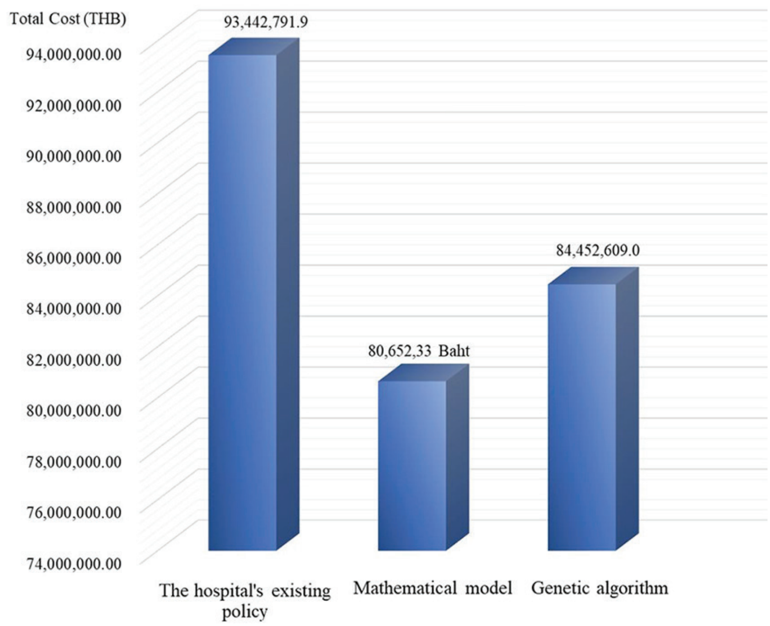



**Figure 4** Comparison of the total cost of drug inventory management in hospitals

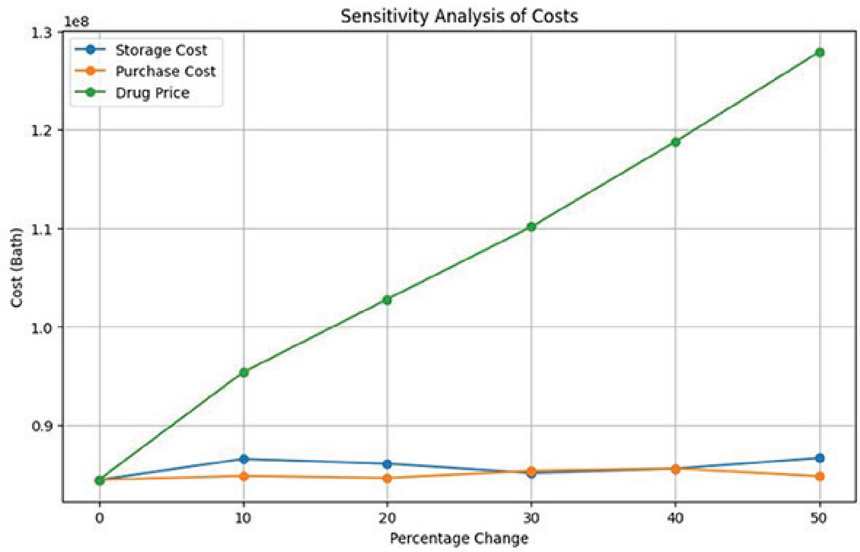



**Figure 5** Sensitivity analysis of cost based on variations in storage costs, ordering costs, and drug prices

A sensitivity analysis of drug inventory costs was conducted to examine the impact of percentage changes in holding costs, ordering costs, and drug prices on the total expenditure of the drug inventory system. As shown in Figure 5, an increase in holding and ordering costs within the range of 10% to 50% resulted in only a minor change in total expenditure. In contrast, changes in drug prices had a direct and significant impact on the total expenditure of the drug inventory. This relationship was further analyzed using the equation y=0.1x, where x represents the percentage change in drug prices and y represents the corresponding percentage change in total expenditure. In this study, scenarios were simulated by adjusting x within the range of 0% to 50% to reflect potential real-world fluctuations in drug prices. The results clearly demonstrate that as drug prices increase, the total expenditure of the drug inventory rises proportionally, and at a steeper rate compared to changes in other cost categories. Adapting to increased costs helps hospital administrators effectively adjust to changing circumstances. However, the likelihood of a significant increase in drug prices is currently low, as this is a factor beyond the hospital's control. Drug price increases depend on the sellers, the Government Pharmaceutical Organization, or the pharmaceutical companies that set the prices. This means hospitals must closely monitor and track price trends to strategically adjust their cost management strategies. Hospitals should focus on negotiating with suppliers to secure the most appropriate prices.

## Discussion

This study applied the K-Means clustering method to classify drugs based on 3 key factors: (1) drug cost (THB), (2) the CV in dispensing volume, and (3) drug importance based on VEN analysis. These factors were selected because they represent essential dimensions for effective drug inventory management in hospitals. Drug cost reflects financial impact, CV indicates demand variability, and VEN analysis prioritizes drug importance for patient care.

Previous studies predominantly utilized ABC analysis to classify drugs according to consumption value, with a particular focus on Group A drugs, which account for the majority of costs and require close monitoring through the Economic Order Quantity (EOQ) and Reorder Point (ROP) methods[8,9]. Subsequently, the integration of ABC and VEN analyses has been recommended to enhance the efficiency of drug inventory management by considering both the financial and clinical significance[10,11]. Several studies have demonstrated that applying ABC-VEN analysis in combination with EOQ can significantly reduce inventory costs[12]. However, it has also been reported that the EOQ approach may not be suitable for products with uncertain demand, as it can lead to increased inventory costs[15]. To address this limitation, this study incorporated demand variability, specifically through the coefficient of variation, into drug classifications. This approach enables the clear distinction between drugs with stable demand and those with uncertain demand, thereby supporting more effective inventory management[17-19].

This study shows that the application of a genetic algorithm (GA) to calculate the optimal order quantity and reorder point can significantly reduce the total cost of hospital drug inventory. The results reflect a clear improvement over traditional hospital drug inventory management methods, which is consistent with previous research that applied GA in the fields of warehouse and pharmaceutical management. These studies found that GA can effectively increase cost efficiency and address various complex problems, such as shelf life, demand uncertainty, and budget constraints[20-22]. Similarly, previous research in the broader supply chain and inventory management domain has explored using advanced optimization models, grey systems, and game-theoretic approaches to manage uncertainty, improve decision-making, and reduce operational costs[23-26]. In addition, the use of emerging technologies such as blockchain and complex routing models has been explored to enhance supply chain transparency and efficiency[27-28].

From a managerial perspective, applying GA in this hospital case study offers clear advantages. GA is a reliable decision-making support tool that helps administrators optimize ordering policies, reduce the total cost of drug inventory, and increase the effectiveness of allocating limited financial resources to enhance overall efficiency. Hospitals can utilize the saved resources in other important areas, such as improving the quality of medical care or purchasing additional medical equipment. In addition, the speed of GA provides flexibility in planning and practical decision-making, especially during times of high uncertainty, such as public health crises or budget constraints.

However, the actual implementation of GA requires consideration of several important factors. The accuracy and completeness of the input data, especially information on drug demand variability and drug prioritization, are essential for the model to be effective. Incomplete or incorrect data may result in poor-quality results. In addition, public hospitals, such as the hospital in this case study, may have limitations in technological infrastructure, personnel, and support systems. Therefore, the effective and sustainable implementation of GA requires investment in personnel training, technology development, and continuous performance monitoring.

This study demonstrates that combining drug grouping techniques with GA is an effective and feasible approach to improving hospital drug inventory management. However, to maximize the benefits of this approach, hospital administrators should be aware of the limitations related to data quality, technological infrastructure, and the need for continuous system monitoring and evaluation.

## Conclusion

Genetic algorithms and mathematical models are used to determine the optimal order quantity and reorder point for the hospital's drug inventory. Both approaches can reduce the total cost of drug inventory compared to the hospital's original purchasing policy. However, the genetic algorithm requires less processing time, reflecting the potential of such approaches for practical application, especially in public hospitals with budget constraints and uncertainty in drug demand.

However, this research still has limitations, as the developed models rely on several simplifying assumptions, such as constant lead time, constant storage costs, and independent demand for each drug. Although these assumptions are necessary for creating and solving mathematical models efficiently, in reality, there may be other, more complex factors, such as relationships between drug items and costs that tend to fluctuate depending on the situation.

Therefore, future research should focus on developing more flexible models that incorporate factors such as variable lead times, fluctuating demand patterns, storage space constraints, and the application of other metaheuristic techniques or hybrid approaches to improve solution quality and increase their suitability for practical use. Although this research has some limitations, the proposed method enables hospital administrators to make better decisions, ultimately improving public health services in the long term.

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## Conflict of interest

The authors declare no potential conflicts of interest concerning the research, authorship, or publication of this article. Additionally, the authors confirm the absence of any financial interests or personal relationships that could have influenced the study's findings or interpretations.

## References

1. Bijvank M, Vis IF. Inventory control for point-of-use locations in hospitals. J Oper Res Soc 2012;63:497-510.
2. Maestre JM, Fernández MI, Jurado IJC. An application of economic model predictive control to inventory management in hospitals. Control Eng Pract 2018;71:120-8.
3. Hughes D, McGuire A. Stochastic demand, production responses and hospital costs. J Health Econ 2003;22:999-1010.
4. Darmian SM, Fattahi M, Keyvanshokooh E. An optimization-based approach for the healthcare districting under uncertainty. Comput Oper Res 2021;135:105425.
5. Caulder CR, Mehta B, Bookstaver PB, Sims LD, Stevenson B, South Carolina Society of Health-System Pharmacists. Impact of drug shortages on health system pharmacies in the Southeastern United States. Hosp Pharm 2015;50:279-86.
6. Hasachoo N, Sirisawat P, Kaewket T. Inventory replenishment policy for medicines with non-stationary stochastic demand: the case of a newly opened hospital in Thailand. In: Proceedings of the 2019 IEEE International Conference on Industrial Engineering and Engineering Management; 2019. p. 89-93.
7. Nigah R, Devnani M, Gupta AK. ABC and VED analysis of the pharmacy store of a tertiary care teaching, research and referral healthcare institute of India. J Young Pharm 2010;2:201-5.
8. Anurattananon C, Klomjit P, Promtong P, Lekkul R. Medicine ordering scheduling in public hospital: case study of Sirindhorn Hospital. Thai Ind Eng Netw J 2020;6:8-19.
9. Mapong K, Moolasarn S, Saohin W, Jaturapattarawong A. Simulation study to determine purchasing methods to reduce drug inventory total cost: a case study at Warinchamrab Hospital. J Health Sci Thail 2014:1077-86.
10. Kritchanchai D, Meesamut W. Developing inventory management in hospital. Int J Supply Chain Manag 2015;4:11-9.
11. Thawani VR, Turankar AV, Sontakke SD, Pimpalkhute SV, Dakhale GN, Jaiswal KS, et al. Economic analysis of drug expenditure in government medical college hospital, Nagpur. Indian J Pharmacol 2004;36:15-9.
12. Mahatme MS, Hiware SK, Shinde AT, Salve AM, Dakhale GN. Medical store management: an integrated economic analysis of a tertiary care hospital in Central India. J Young Pharm 2012;4:114-8.
13. Takawira B, Pooe RI. Supply chain disruptions during COVID-19 pandemic: key lessons from the pharmaceutical industry. South Afr J Bus Manag 2024;55:4048.
14. Denizhan B, Yıldırım E, Akkan Ö. An order-picking problem in a medical facility using genetic algorithm. Processes 2024;13:22.
15. Junita I, Sari RK. ABC-VED analysis and economic order interval (EOI)-multiple items for medicines inventory control in hospital. In: Proceedings of the 2012 International Conference on Business and Management; 2012 Sep. p. 6-7.
16. Du M, Luo J, Wang S, Liu S. Genetic algorithm combined with BP neural network in hospital drug inventory management system. Neural Comput Appl 2020;32:1981-94.
17. Demiray Kırmızı S, Ceylan Z, Bulkan S. Enhancing inventory management through safety-stock strategies: a case study. Systems 2024;12:260.
18. Syntetos AA, Boylan JE, Croston JD. On the categorization of demand patterns. J Oper Res Soc 2005;56:495-503.
19. Lukinskiy V, Lukinskiy V, Sokolov B. Control of inventory dynamics: a survey of special cases for products with low demand. Annu Rev Control 2020;49:306-20.
20. Rajendran S, Ravindran AR. Inventory management of platelets along blood supply chain to minimize wastage and shortage. Comput Ind Eng 2019;130:714-30.
21. Gonçalves JN, Carvalho MS, Costa L. Improving inventory management in an automotive supply chain: a multi-objective optimization approach using a genetic algorithm. In: Proceedings of Congress of APDIO, the Portuguese Operational Research Society; 2018 Sep. p. 143-57.
22. Çelebi D. Inventory control in a centralized distribution network using genetic algorithms: a case study. Comput Ind Eng 2015;87:532-9.
23. Liu Y, Liu J, Wu X, Liu J, Ma J, Song W. Pricing model of two-echelon supply chain for substitutable products based on double-interval grey numbers. Appl Math Model 2021;93:264-85.
24. Hendalianpour M. Optimal lot-size and price of perishable goods: a novel game-theoretic model using double interval grey numbers. Expert Syst Appl 2022;200:116919.

25. Zhao Z, Zhang Y, Liu X, Zhang J. A solution algorithm for integrated production-inventory-routing of perishable goods with transshipment and uncertain demand. Expert Syst Appl 2022;206:117709.
26. Hajipour V, Rabbani M, Mahmoudzadeh S, Iranmanesh H. Cost reduction of inventory-production-system in multi-echelon supply chain using game theory and fuzzy demand forecasting. J Ind Inf Integr 2020;18:100148.
27. Zhang X, Zhao H, Zheng J, Li Y, Hu K. Mathematical modeling of vehicle routing problem in omni-channel retailing. Expert Syst Appl 2022;190:116184.
28. Li Z, Zhang D, Tang C, Liu H, Wang X, Yang Q, et al. Factors affecting the use of blockchain technology in humanitarian supply chain: a novel fuzzy large-scale group-DEMATEL. Soft Comput 2020;24:17961-79.