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A Dynamic Simulation-Optimization Approach for Inventory Management of Multi-Product Hospital Pharmacies in Discrete Time

Hamed Jabarie [1], Hamid Shahbandarzadeh✉ [2], Ahmad Ghorbanpour [3], and Habib Omraniakhoo[4]

1. PhD in Industrial Management, Mathematics Secretary of Education, Bushehr, Iran. E-mail: mmjabbari94@gmail.com
2. Corresponding author, Associate Prof., Department of Industrial Management, Faculty of Business and Economics, Persian Gulf University, Bushehr, Iran. E-mail: Shahbandarzadeh@pgu.ac.ir
3. Assistant Prof., Department of Industrial Management, Faculty of Business and Economics, Persian Gulf University, Bushehr, Iran E-mail: ah.ghorbanpur@gmail.com
4. Assistant Prof., Department of Nutrition, Faculty of Health, Bushehr University of Medical Sciences and Health Services, Bushehr, Iran. E-mail: habibomranikho@yahoo.com

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ABSTRACT

Objective: In the patient care chain, medicines are essential items and play a critical role in patient recovery. Inefficient inventory management leads to drug shortages, lack of continuity of drug inventory, reduced patient safety, poor performance, distribution defects, and technological errors, which lead to drug shortages in hospital pharmacies. Providing an efficient approach can minimize costs in the supply chain.

Methods: This study presented a simulation-optimization model for pharmacy inventory management. A training-learning-based optimization algorithm was used to solve the model. The model was programmed and solved in MATLAB software.

Results: Given that the initial inventory is assumed to be zero, the drug price is lower at the beginning of the year, and the number of patients is lower than in the summer. Therefore, the volume of orders is high at the start of the year. The model adjusts the level of orders so that the costs are minimal. As the disease re-emerges and the number of patients increases, demand increases in the ninth and tenth months, and the volume of orders increases again. As demand decreases at the end of the year, the volume of orders also decreases.

Conclusion: By implementing the model during the planning period, while minimizing system costs, the inventory level for all drug categories will be at the desired level, and no inventory shortages will occur.

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Introduction

The patient treatment chain is subject to numerous variables, among which medicine is one of its essential items and plays a significant role in improving patient outcomes. Continuous access and continuity of access to the drugs needed by patients and the absence of interruption in the supply of the required medicines are among the critical management issues in hospitals (Chen et al, 2022; Abu Zwaida et al, 2021). Studies show that between 20% and 25% of hospital costs are related to drug cost centers(Gebicki et al, 2014). Therefore, drug inventory management in hospitals is of particular importance, both from the perspective of the treatment process and the health economy. Healthcare centers worldwide are looking for ways to improve the efficiency of their operations (Wild, 2017). Healthcare providers are striving to optimize their inventory management, which will reduce costs associated with providing healthcare services (Qiu et al, 2019). In cases where clients are unable to access essential pharmaceutical products, physicians have a duty to inform them of the reasons for the unavailability of the product, when the product will be available, the options available for the available pharmaceutical product, the associated costs, and how to obtain the available product. However, it is worth noting that drug shortages are unacceptable for hospitals (Shiau et al, 2019). Traditional methods of drug inventory management can always present hospitals with serious challenges, such as over- or under-estimating the need. Excessive demand can negatively impact hospital finances and, in some cases, lead to drug expiration and waste of resources. On the other hand, drug shortages can also cause interruptions in patient treatment and disrupt the patient's recovery process. Therefore, determining the optimal level of drug ordering and pharmacy inventory management can effectively prevent these problems (Chen et al, 2022). So far, two classification methods have been used in healthcare facilities to manage drug inventory and identify different levels of importance from a storage perspective. In both methods, drugs are classified into different categories and indicate different levels of importance among drugs (Antonoglou et al, 2017). In addition to drug identification, determining drug inventory levels is a crucial step for optimal management. Good inventory regulation and control stabilize inventory operations and ensure drug supply (Hejazi, 2021). Another point is that most early inventory management models in the healthcare sector considered static conditions. In contrast, real-world issues are complex and dynamic. The spread of epidemics, increasing demand for medicines and services, and the existence of economic difficulties in supplying them are the main reasons for the complexity of the issues.

This study investigates the drug inventory optimization problem in the Persian Gulf Martyrs Hospital pharmacy, which can minimize the constraints of drug demand, storage capacity, reorder conditions, and reorder costs. Since the designed problem is NP-hard, finding a solution in polynomial time is impossible. To overcome this problem, evolutionary algorithms can be used. In all algorithms based on intelligent and evolutionary sets, it is inevitable to determine the usual control parameters, including population size and production number. Control parameters specific to that algorithm must also be determined in various algorithms, in addition to the standard parameters. Choosing the correct values of the control parameters is very sensitive and dramatically affects the algorithm's performance. In addition, choosing the wrong parameters may cause the calculations to be over-optimized or give local optimal responses. One of the newest optimization algorithms is the teaching learning based optimization algorithm, which, inspired by the natural process of teaching and learning, performs optimization operations without the need to determine a specific control parameter (Rao et al, 2010). This study is innovative in presenting a multi-case discrete-time dynamic optimization simulation model for inventory level management and employing a training-learning algorithm to solve the model. Dynamic simulation-optimization refers to using dynamic simulation models to optimize a system. It involves continuously running simulations based on variables and changing conditions, and then using optimization techniques to find the best solution or set of solutions to improve the system's performance. This approach enables more accurate and real-time decision-making in complex and dynamic systems.

The research structure is as follows: The theoretical and empirical background in drug inventory management will be reviewed in the second section. In the third section, the multi-product dynamic simulation model will be presented, and the steps of the algorithm based on training and iterative learning will be described. In the fourth section, the numerical results obtained from the implementation of the algorithm will be presented, and the algorithm's performance will be compared. Finally, the research results and suggestions for future research will be presented.

Literature Background

Several studies have been conducted on drug inventory management in the past decade. Some of them are as follows: Saedi et al. (2016) presented a mathematical programming model with constraints including delivery time, stochastic drug demand, and alternative drugs. This study proposed a two-stage heuristic algorithm to solve their mathematical programming model and calculate cost, inventory space, drug shortage rate, and safe inventory. It used pharmaceutical data from a Houston, Texas hospital for validation. Guerrero et al. (2013) presented a heuristic algorithm to solve the optimal order quantity of each product for an inventory strategy in a central pharmaceutical warehouse. Their research compared the developed method with the inventory strategy of the studied hospital and found that inventory costs were reduced by about 45% while maintaining a good level of service quality. Buschiazzo et al. (2020) investigated the inventory optimization problem of medical equipment for cardiac surgery.

They considered procurement strategies (such as precautionary inventory, available budget), actual warehouse space (such as warehouse capacity), and characteristics of medical equipment (such as lifespan and service level) and suppliers (such as price, supply quantity, and minimum order quantity); they used mathematical programming to build a mixed integer programming model of the inventory of medical equipment for cardiac surgery. They used the CPLEX algorithm to solve the cost minimization problem model. The mathematical programming results were compared with the system simulation results, and the corresponding sensitivity analysis was performed. The managerial implications of the research were also discussed to enhance the practical value of the results.

Galli et al. (2021) proposed an optimization method for drug replenishment in a hospital ward. The proposed model uses machine learning combined with stochastic optimization to consider both historical drug usage patterns and the current state of the ward to minimize inventory levels and the need for emergency replenishment.

Elarbi et al. (2021) propose a collaborative multi-tier pharmaceutical supply chain consisting of a central pharmacy, multi-regional pharmacies, and multiple hospitals using a multi-period, multi-product stochastic mathematical model to minimize shortage and holding costs for drug inventory management. The stochastic mathematical model is solved using Lingo software and the branch-and-bound method. Chen et al. (2022) combined a two-stage clustering method with an inventory policy and developed a simulation optimization model for the study hospital's outpatient pharmacy. This study used Arena optimization-simulation software to determine the minimum and maximum values of the best inventory quantities for each drug: cost considerations and related inventory constraints. The study results showed that the minimum and maximum inventory settings for each drug in the simulation model were better than those of the study pharmacy system. The average inventory cost was reduced by 55% while the average inventory volume was reduced by 68%.

Ben Chihaoui et al. (2019) conducted a study to optimize medical management to reduce drug inventory costs and improve patient satisfaction. The main issues in extensive inventories were: drug shortages, overstocking, discrimination in the healthcare system, unfunded estimation techniques, and lack of knowledge. This study presents a real-world case study that aims to automate product inventory management and distribution while reducing drug shortages and production costs. A fuzzy decision support system is also implemented to help users improve drug inventory management and make reliable decisions for better patient satisfaction.

Materials and Methods

This research employs a developmental-applied methodology, emphasizing collecting empirical data directly from the field. The study analyzes secondary data obtained from Persian Gulf Martyrs Hospital in Bushehr. The analytical framework for this research is rooted in an analytical-mathematical method, specifically drawing upon Walker's classification system as its foundation. The primary objective of this research is to gain a comprehensive understanding of the dynamic changes occurring within the hospital's system. This involves thoroughly examining the intricate relationships and interdependencies between the hospital's various internal components and elements. Furthermore, the research endeavors to construct a dynamic model that effectively represents and elucidates the complex interactions within the hospital system. This methodological approach is consistent with the principles and tenets of complexity theory, as articulated by Walker in 1998, providing a theoretical lens through which to interpret the empirical findings and understand the emergent properties of the hospital as a complex adaptive system. The application of complexity theory allows for a nuanced understanding of how the hospital adapts and evolves, responding to internal and external pressures.

Since the present issue is NP-hard, a teaching-learning-based algorithm has been used to solve and implement the simulation-optimization model. Inventory is important in producing and organizing logistical support in public companies. Inventories in factories, wholesalers, retailers, and hospitals must be managed. In order to respond to uncertain future demands, the business community stores appropriate amounts of materials, which is the goal of inventory management. Fogarty and Hoffmann (2021) noted that inventory management is developed under uncertainty in demand and supply regarding time and quantity. Inventory costs include holding costs, storage costs, ordering costs, and the cost of inventory.

Simulation-Optimization

Simulation-optimization is a powerful approach, particularly beneficial for dynamic optimization problems. A critical prerequisite for successful dynamic optimization is the availability of a dynamic model that accurately represents the system under study. Identifying and selecting an appropriate dynamic model are of utmost importance, serving as the bedrock upon which the entire optimization process is built. In many cases, the development of such a model begins with constructing a static model. This initial static representation is progressively enhanced and refined by incorporating dynamic elements. These dynamic elements are carefully chosen to capture the system's evolution over time, reflecting the changes and interactions within the system as it operates.

The simulation-optimization approach is characterized by a significant degree of diversity, with numerous variations and implementations possible. Consequently, the specific design and implementation of a simulation-optimization strategy should be meticulously tailored to align with the specific characteristics and nuances of the problem being addressed. There are generally three key features that define simulation-optimization problems. First, evaluating each objective function typically necessitates a series of simulation iterations. These iterations are crucial for accurately assessing the system's performance under different conditions and parameter settings. Second, these simulation iterations can be time-intensive, requiring significant computational resources.

The computational demand becomes particularly pronounced when dealing with simulation models that are complex, large-scale, or involve intricate interactions between numerous components (Figueira, 2014). Finally, the optimization algorithms must be carefully chosen to handle the stochastic nature of simulation outputs. The inherent variability in simulation results can make converging to an optimal solution challenging for traditional optimization methods.

In the context of the present study, a simulation model has been integrated with the teaching-learning based optimization (TLBO) algorithm. This integrated approach is specifically designed to optimize inventory management within a hospital pharmacy. The goal is to improve the efficiency and effectiveness of inventory control, ensuring that medications and supplies are readily available when needed while minimizing waste and storage costs.

Mathematical Model

This inventory control model aims to:

- Minimize the costs of storing and ordering drugs.
- Prevent drug shortages during the simulation.
- Acknowledge that drug storage and ordering costs change over time.
- Ensure order quantities are large enough to satisfy the hospital pharmacy's drug needs.
- Avoid inventory shortages.
- Account for warehouse space limitations.
- Consider time as a dynamic factor in decision-making.

The following components define the model:

Indices:

k: Index of the drug number, where k=1, 2, ..., K

t: Index of time periods, where t=1, 2, ..., T.

Parameters:

$OC_{k.t}$: Ordering cost of the kth drug at time t.

$HC_{k.t}$: Holding and storage cost of the kth drug at time t.

$D_{k.t}$: The demand for the kth drug at time t.

UR_k: Upper limit of the maximum amount of the kth.

NL: Lower limit on the number of orders for all.

NU: Upper limit on the number of orders for all drugs.

$u_k: Volume\ of\ kth\ drug.$

u_{max}: Maximum pharmacy warehouse capacity.

T: Time horizon.

Decision variables

$X_{k.t}$: Order quantity of the kth drug at time t.

$I_{k.t}$: Inventory of the kth drug at time t.

S_k: Minimum amount of drug kth.

R_k: Maximum amount of drug kth.

Z: Total cost.

The system state at each step depends on the system state at the previous step, and an appropriate decision must always be made. At any given moment, the inventory level of each type of drug is equal to the order quantity minus the demand for that drug, plus the previous inventory level for the next period. In this model, relation (1) is the objective function to minimize drug holding and ordering costs for each period. Equation (2) establishes the dynamic relationship between inventory, demand, and order quantity of all drugs in the present time and inventory in the past, across all time steps, and represents the flow conservation of each drug in all time periods. Relation (3) represents the inventory of each drug at the beginning of the simulation period. Relation (4) requires a positive inventory level in each period to meet the drug needs of patients. Relation (5) satisfies the warehouse capacity constraint in each time step, considering the volume occupied by each type of drug. Relations (6) and (7) show the lower and upper bounds of the total number of drug orders, respectively. Relation (8) shows that the minimum quantity of each drug is less than the maximum quantity of each drug. Relation (9) shows that the maximum quantity of each drug has an upper bound. Relations (10) - (14) consider the decision variables as integers. It is worth noting that, in the presented model, the dynamic equation (2) expresses a system in which I is the inventory level, X is the order quantity, D is the demand rate, and t represents time, in relation (15).

$$I_t = I_{t-1} + X_t - D_t \tag{15}$$

Assuming I_0 (initial inventory) is known, the values of I_k (inventory of the kth period) are calculated recursively using relations (16) to (19). In these relations, X is a decision variable.

$$I_1 = I_0 + X_1 - D_1 \tag{16}$$
$$I_2 = I_1 + X_2 - D_2 \tag{17}$$
$$I_3 = I_2 + X_3 - D_3 \tag{18}$$
$$I_k = I_{k-1} + X_k - D_k \tag{19}$$

Therefore;

$$I_k = I_0 + \sum_{j=1}^{k} X_{k_1} - \sum_{j=1}^{k} D_k \tag{20}$$

Teaching-learning based optimization (TLBO) algorithm

One of the newest optimization algorithms that performs optimization operations without the need to determine specific control parameters. This algorithm was first presented by Rao et al. (2010), inspired by the natural teaching and learning process. The very high capability of this algorithm in solving complex, non-linear, and multi-objective mathematical problems has led to its widespread use. Yu et al. (2016), Garcia and Mena (2016), Chen et al. (2015), Akbari et al. (2022), and Di Wu et al. (2022) have used the teaching-learning-based optimization algorithm to optimize their problems. The teaching-learning-based optimization algorithm is based on the teacher's effect on students' performance in a class. This algorithm considers a mathematical model for teaching and learning, and the optimization process is performed in two stages. The upper and lower bounds of the variables, the number of generations, and the fitness function are the inputs of this algorithm. This algorithm includes two stages as follows:

a) Teaching Phase: In this stage, the class members are generated according to the bounds of the variables. The best member of the population is selected as the teacher or instructor. The teacher tries to increase the average of the class by influencing the knowledge level of the class members to increase their level and direct the population mean towards themselves. This is similar to what a teacher actually does in the real world. If T_i is the teacher and M_i is the average class level in the (i)th iteration, and after the teacher's training, the new average improves. Therefore, the new average T_i is determined as M_{new} using relation (21):

$$\text{Difference} - Mean_{\mathrm{i}} = r_{\mathrm{i}}(M_{\mathrm{new}} - T_{\mathrm{F}} M_i) \tag{21}$$

In relation (21), T_{F} the training factor determines the quality of training and the professor's ability to transfer knowledge. The value of T_{F} can be 1 or 2, which is an exploratory step and is randomly determined with equal probability according to relation (22):

$$T_{\mathrm{F}} = round[1 + round(0.1)\{1.2\}] \tag{22}$$

r_{i} is also a random number in [0,1]. This difference updates the existing answers according to relation (23).

$$X_{\mathrm{new,i}} = X_{\mathrm{old.i}} + \text{Difference} - Mean_{\mathrm{i}} \tag{23}$$

b) Learning Phase: In this phase, the individuals in the population (considered classmates) collaborate to develop their knowledge. This is similar to what actually happens among friends and classmates. The algorithm's process in the second phase is that two class members randomly interact with each other, and the knowledge gained from their interaction affects the knowledge level of other students in the class. The extent of this impact on the learning phenomenon is expressed mathematically below. In each iteration i, considering two different learners $\mathrm{X_i}$ and $\mathrm{X_j}$ where $\mathrm{i} \neq \mathrm{j}$ Is determined based on relation (24):

$$\begin{cases} X_{\mathrm{new,i}} = X_{\mathrm{old,i}} + r_i(X_{\mathrm{j}} - X_{\mathrm{i}}) & if\ f(X_{\mathrm{i}}) < f(X_{\mathrm{j}}) \\ X_{\mathrm{new,i}} = X_{\mathrm{old,i}} + r_i(X_{\mathrm{i}} - X_{\mathrm{j}}) & if\ f(X_{\mathrm{j}}) < f(X_{\mathrm{i}}) \end{cases} \tag{24}$$

Results

This study used a personal computer with an AMD A10-5745M APU Graphics 3.10 GHz processor, 12 GB of RAM, Windows 10, and MATLAB 2018 software. A data-driven system simulation model was developed to analyze medication requirements for patients, specifically within the Corona ward of Bushehr's Persian Gulf Martyrs Hospital. The simulation duration was established as one year, with the progression of time occurring in discrete monthly intervals. An intelligent optimization algorithm was employed to optimize the simulation results, and the number of repetitions for this optimization process was configured to 500 iterations. The methodology for determining drug demand adhered to the established hospital protocols, wherein the demand for each medication is derived from the comprehensive drug lists prescribed by the attending physicians. The primary focus of this research initiative centered on the medication inventory information system, specifically concerning the patient population within the Corona ward. The model aimed to replicate and analyze the flow of medications, predict potential shortages or overstocks, and optimize the inventory management process within this critical hospital unit. The simulation provided a virtual environment to test different inventory strategies and assess their impact on medication availability and cost-effectiveness, all based on the real-world data and processes of the hospital's Corona ward. The ultimate goal was to improve the efficiency and effectiveness of the medication supply chain for these patients.

All medication orders issued by the mentioned hospital section were collected and aggregated, as the medication demand was created daily and monthly. Medications are categorized according to their dosage form. The eight most frequent different dosage forms of medications are: tablets, suspensions, solutions, suppositories, capsules, syrups, gels, ointments, and powders. In this study, 78 drugs were examined from April to March 2021. Demand, purchase cost, maintenance and storage cost, upper and lower limits of the number of orders, volume occupied by each drug, and warehouse capacity after estimation are considered model inputs. In order to evaluate the performance of the Teaching-Learning-Based Optimization (TLBO) algorithm in the simulation-optimization process, the model was also run using the Particle Swarm Optimization (PSO) algorithm, and the results were compared. In Figure 1, the execution of the model by the Teaching-Learning-Based Optimization and Particle Swarm Optimization algorithms is observed. The algorithm effectively obtained the minimum of the cost function in 225.95 seconds. The value of the cost function at iteration 500 is 1.328e+11.

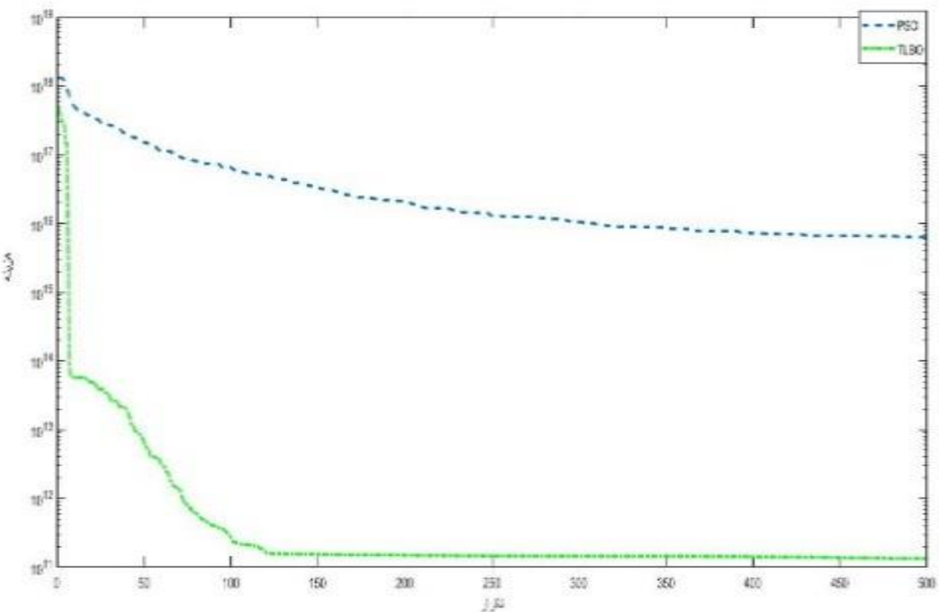

Figure 1. Iteration-cost figure of TLBO and PSO algorithms

To evaluate the performance of the Teaching-Learning-Based Optimization algorithm, the model was executed using the Particle Swarm Optimization algorithm with the same population size as the Teaching-Learning-Based Optimization algorithm and with the parameters suggested by Kennedy and Clerc (2002) in 500 iterations and 310.25 seconds. The Particle Swarm Optimization algorithm could not find the optimal solution with these parameters. The lowest value of the cost function is 6.3040e+15. Furthermore, in Figure 2, the right side shows the warehouse capacity, and the left shows the volume filled. It is observed that this algorithm, with these parameters, has not been able to comply with the warehouse volume constraint in most time steps. Based on the above, the TLBO algorithm can perform the simulation-optimization process without adjusting any specific parameters and find a near-optimal solution for the problem.

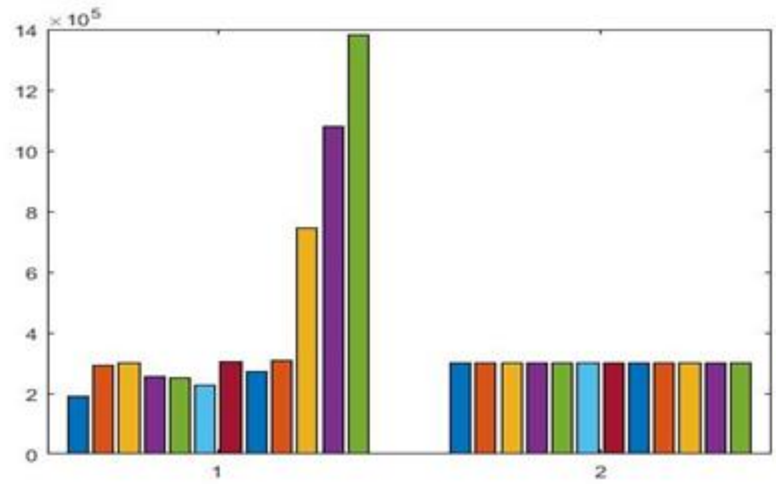

Figure 2. Capacity (1) and volume (2) of the warehouse in the implementation of the PSO algorithm

Figure 3 shows the monthly order quantity of different drug categories in the desired time steps. The data for these changes are also presented in Table 1. Considering that an initial zero is assumed, the drug's price is lower, and the number of patients is also lower at the beginning of the year compared to the summer. Therefore, the order volume is high at the beginning of the year. The model adjusts the order levels so that the costs are minimized. With the resurgence of the disease and the number of patients, resulting in increased consumption in the ninth and tenth months, the order volume increases again. With consumption at the end of the year, the rate of decrease also decreases. Hospital management can use the simulation results to adjust the order planning in such a way as to pay the lowest cost.

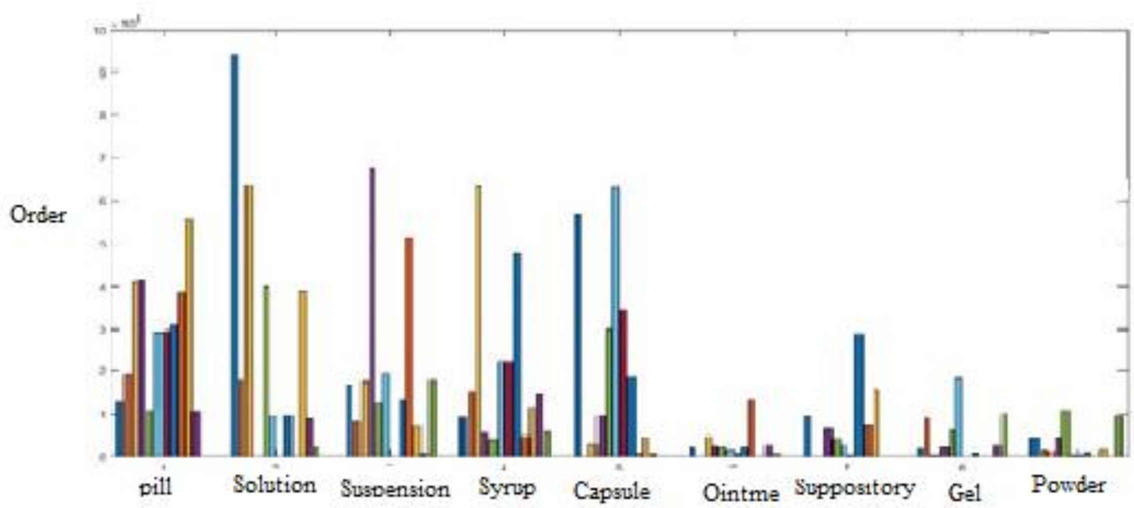

Figure 3. Chart of monthly orders for categorized drugs

Figure 4 illustrates the fluctuation of drug inventory levels across various time intervals. Upon examination, it becomes evident that the inventory level for the solution reaches its zenith during the second and third months. This indicates a period of significant stock accumulation for this particular drug. Subsequently, as we progress into the fourth and fifth months, a notable shift occurs. These months coincide with the peak of the viral outbreak, a period characterized by a substantial surge in demand for pharmaceutical products. Consequently, the prices of drugs within this category experience a sharp and pronounced increase. This price escalation directly results from the heightened demand driven by the viral outbreak. Given these circumstances, the model strives to meet its objectives and adhere to its constraints. To achieve this, the inventory level is strategically maintained at a high level. This proactive measure ensures an adequate supply of drugs to address the escalating demand during the critical outbreak period. The elevated inventory levels reflect an optimized storage strategy to meet future needs effectively. In essence, the observed inventory management practices demonstrate a deliberate and well-considered approach to ensuring drug availability in the face of fluctuating demand and external pressures such as a viral outbreak. This proactive storage strategy is crucial for mitigating potential shortages and maintaining a consistent supply of essential medications to the population.

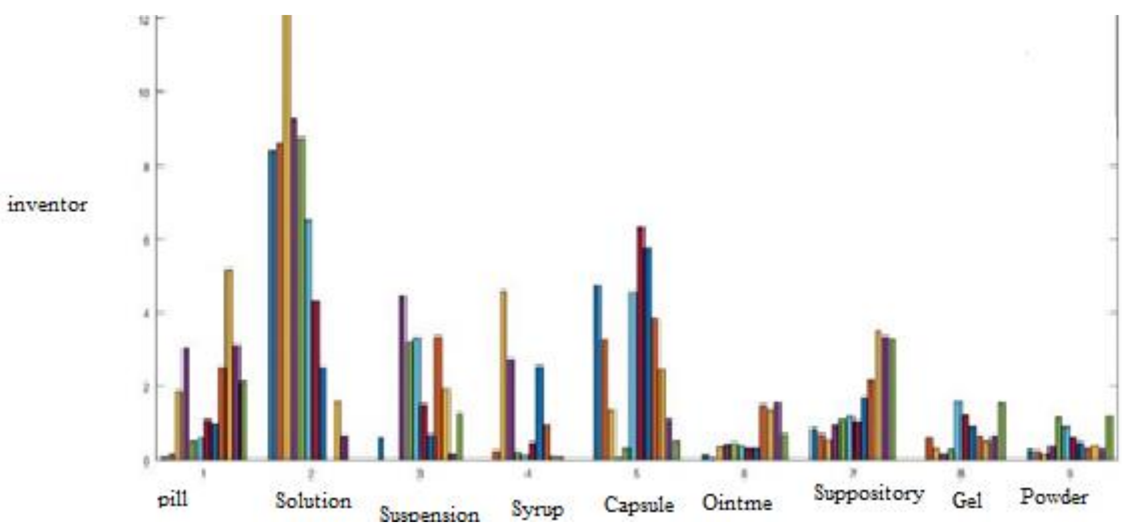

Figure 4. Monthly stock level of categorized drugs

Figure 5 shows the filled volume of the pharmaceutical warehouse. The warehouse capacity is 5+e3. It is observed that the occupied volume of the warehouse is less than the warehouse capacity at all time steps.

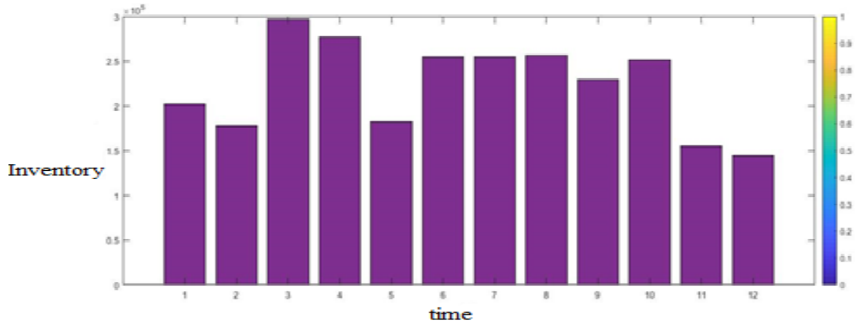

Figure 5. Monthly pharmaceutical stockpiled volume

The algorithm's execution and subsequent problem modeling and optimization simulation have yielded satisfactory results, as evidenced by the data in Table 1 and the visual representations in graphs 3 and 4. Specifically, Table 1 provides a detailed report of the numerical values underpinning the trends and patterns in the aforementioned graphs. This numerical data serves to quantify the relationships observed within the simulation. A key observation from Table 1 and graphs 3 and 4 analysis is the clear proportionality between the number of orders, the price, and the demand for the drug across all time periods considered in the simulation. This proportionality suggests a strong correlation between these factors, indicating that as the price and demand for the drug fluctuate, the number of orders responds predictably and consistently. The successful completion of these steps confirms the validity and reliability of the modeling approach used in this study.

Table 1. Order volume, inventory level, and occupied warehouse volume in time steps

period	1	2	3	4	5	6	7	8	9	10	11	12	Pharmacy
Order	12726	18898	41019	41698	10758	28929	29884	30724	38534	55567	10439	0	pill
	93871	18013	63671	32	39998	9602	7	9774	7	38930	8737	2318	Solution
	17703	8160	17788	67321	12609	19130	185	13559	51514	6848	466	17992	Suspension
	9124	15249	63434	5579	3718	22324	22327	47648	5181	11329	14839	5933	Syrup
	56406	176	3077	9737	29968	63312	34547	18505	714	4544	521	0	Capsule
	2166	146	4942	2755	2543	1505	382	2147	13556	134	2874	641	Ointment
	9453	92	59	6444	3971	2872	276	28461	7236	15749	0	108	Suppository
	2013	9004	332	2421	6063	18246	153	808	150	14	2825	10189	Powder
	4223	1511	1184	4355	10673	304	186	997	2	1820	49	9556	Gel
Inventory	726	1624	18643	30341	5099	6028	10912	9636	25170	51737	31176	21176	pill
	83871	85884	125645	92677	87675	65277	43284	25058	65	15995	6732	50	Solution
	6073	233	21	4434	31951	33081	15266	6825	33339	19187	1653	12645	Suspension
	124	2373	45807	27386	2104	1428	4755	25403	9584	913	752	185	Syrup
	47406	32582	13659	396	3364	45676	63223	57728	38422	24486	11007	5007	Capsule
	1466	412	3554	4309	442	4157	3139	3286	15042	13629	15400	7041	Ointment
	8353	7045	5304	9448	10919	11991	10467	16928	21664	35313	33513	32921	Suppository
	13	6017	3349	1770	2833	16079	12232	9040	5204	5204	6529	15518	Powder
	2743	2454	1638	3893	11566	9070	6256	4853	3975	3975	3024	11780	Gel
Filled capacity	155744	177657	297367	276578	182096	276578	254680	256377	229902	251547	155745	144471	

The data presented in the table above, derived from our inventory management optimization simulation model, strongly suggests its suitability for effectively managing the supply requirements of a hospital pharmacy. A thorough examination of the numerical results reveals that the model maintains optimal inventory levels across all drug categories and specified time periods. This is achieved while simultaneously minimizing the total costs associated with the inventory management system. Specifically, the simulation demonstrates that the model successfully ensures that the inventory levels for each drug category are consistently maintained at their ideal quantity during each time period analyzed. Furthermore, a critical outcome of the simulation is the complete absence of any inventory shortages. This indicates that the model's optimization strategies are robust enough to prevent stockouts and guarantee the continuous availability of essential medications while adhering to the objective of cost minimization within the pharmacy's inventory management framework.

Discussion and Conclusion

Hospital pharmacy inventory management is a key issue, especially in crises, and can reduce costs without affecting medical care and services. Inefficient inventory management leads to drug shortages, inventory discontinuity, reduced patient safety, poor performance, distribution defects, and technological errors, resulting in drug shortages in hospital pharmacies. Providing an efficient method can minimize costs in the drug supply chain and prevent shortages. In this study, 78 drugs were examined for categorization to manage hospital pharmacy inventory. In previous research, Scott et al. (2021) used statistical methods, and Bushiazzo et al. (2020) used a sectional optimization approach in hospital inventory management. This research proposes a simulation-optimization approach to solve the hospital drug inventory control problem, which can consider drug reordering requirements, meet warehouse volume constraints, and minimize purchasing and storage costs. The model presented in this research has been expanded compared to the research of Chen et al. (2022) and Abu Zwaida (2021) in the field of simulation optimization models, because in the present research, the limitation of drug warehouse volume has been considered, drug categories occupy different volumes of the warehouse, and the cost of ordering and maintenance varies throughout the simulation period. In addition, an intelligent optimization algorithm is used to solve the model.

Utilizing the research results can determine how much of the drug volume should be reordered at any given time to prevent the system from running out of stock while minimizing the organization's costs. Also, to solve the simulation optimization problem, a learning-based optimization algorithm is used, which can execute the process without performing any specific parameter adjustments. Furthermore, comparing the results of the proposed algorithm with the Particle Swarm Optimization algorithm shows favorable performance results.

The current research innovations are: designing a discrete-time dynamic model for hospital pharmacy inventory management and finding the optimal inventory level and order quantities, using a simulation-optimization approach to perform the inventory management process, and using an innovative learning-based optimization algorithm in solving the drug inventory management model. Also, future research can improve the model in more realistic conditions by considering random and fuzzy variables and parameters, and use artificial intelligence and data mining approaches to estimate demand. By considering the rate of drug spoilage, the model can be improved and have the highest possible accuracy in predicting the needs of the hospital pharmacy. In addition, designing intelligent inventory management systems, utilizing new technologies such as the Internet of Things, and using deep learning algorithms are also important strategies for improving hospital pharmacy inventory management, which can accelerate the improvement of pharmacy performance and efficiency. These measures can improve their performance and predict the needs of the pharmacy more accurately. Applying the proposed forward-looking approach is vital for improving hospital pharmacy management systems. If implemented correctly, it can reduce many of the problems and risks associated with managing this sector and increase the efficiency and productivity of pharmacies.

Data Availability Statement

Data available on request from the authors.

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Ethical considerations

The authors have witnessed the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancy.

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Conflict of interest

The authors declare no potential conflict of interest regarding the publication of this work.

References

Abu Zwaida, T., Pham, C., & Beauregard, Y. (2021). Optimization of inventory management to prevent drug shortages in the hospital supply chain. *Applied Sciences*, *11*(6), 2726. *DOI:* 10.3390/app11062726.

Akbari, E., Ghasemi, M., Gil, M., Rahimnejad, A., & Andrew Gadsden, S. (2022). Optimal power flow via teaching-learning-studying-based optimization algorithm. *Electric Power Components and Systems*, *49*(6-7), 584–601. DOI: 10.1080/15325008.2021.1971331.

Antonoglou, D., Kastanioti, C., & Niakas, D. (2017). ABC and VED analysis of medical materials of a general military hospital in Greece. *Journal of Health Management*, *19*(1), 170-179. DOI: 10.1177/0972063416682643.

Buschiazzo, M., Mula, J., & Campuzano-Bolarin, F. (2020). Simulation optimization for the inventory management of healthcare supplies. *International Journal of Simulation Modelling*, *19*(2), 255–266. DOI: 10.2507/IJSIMM19-2-514.

Chen, C. N., Lai, C. H., Lu, G. W., Huang, C. C., Wu, L. J., Lin, H. C., & Chen, P. S. (2022). Applying simulation optimization to minimize drug inventory costs: a study of a case outpatient pharmacy. In *Healthcare*,*10*(3), 556. DOI: 10.3390/healthcare10030556.

Chen, D., Zou, F., Li, Z., Wang, J., & Li, S. (2015). An improved teaching–learning-based optimization algorithm for solving global optimization problems. *Information Sciences*, *297*, 171-190. DOI: 10.1155/2022/1535957.

Chihaoui, F. B., Maddeh, N., Layeb, S. B., Hamouda, C., & Chaouachi, J. (2019, April). A decision support system for drug inventory management within an emergency department: A case study. In 2019, *the 6th International Conference on Control, Decision, and Information Technologies*. IEEE. 1889-1894. DOI: 10.1109/CoDIT.2019.8820599.

Clerc, M., & Kennedy, J. (2002). The particle swarm-explosion, stability, and convergence in a multidimensional complex space. *IEEE Transactions on Evolutionary Computation*, *6*(1), 58–73. DOI: 10.1109/4235.985692.

Elarbi, M., Ayadi, O., Masmoudi, M., & Masmoudi, F. (2021). Drug-inventory-management-model for a multi-echelon pharmaceutical supply-chain: case study of the Tunisian pharmaceutical supply-chain. *In Supply Chain Forum: An International Journal*, *22*(1), 44–56. Taylor & Francis. Chicago. DOI: 10.1080/16258312.2020.1824532.

Figueira, G., & Almada-Lobo, B. (2014). Hybrid simulation–optimization methods: A taxonomy and discussion. *Simulation modelling practice and theory*, *46*, 118–134. DOI: 10.1016/j.ejor.2007.07.035.

Galli, L., Levato, T., Schoen, F., & Tigli, L. (2021). Prescriptive analytics for inventory management in health care, *Journal of the Operational Research Society*, *72*(10), 2211–2224. DOI: 10.1080/01605682.2020.1776167.

García, J. A. M., & Mena, A. J. G. (2013). Optimal distributed generation location and size using a modified teaching–learning optimization algorithm. *International journal of electrical power & energy systems*, *50*, 65–75. DOI: 10.1016/j.ijepes.2013.02.023.

Gebicki, M., Mooney, E., Chen, S. J., & Mazur, L. M. (2014). Evaluation of hospital medication inventory policies. *Health care management science*, *17*(3), 215–229. DOI: 10.1007/s10729-013-9251-1.

Guerrero, W. J., Yeung, T. G., & Guéret, C. (2013). Joint-optimizing inventory policies on a multi-product multi-echelon pharmaceutical system with batching and ordering constraints. *European Journal of Operational Research*, *231*(1), 98–108. DOI: 10.1016/j.ejor.2013.05.030.

Hejazi, T. H. (2021). State-dependent resource reallocation plan for health care systems: A simulation optimization approach. *Computers & Industrial Engineering*, *159*, 107502. DOI: 10.1016/j.cie.2021.107502.

Qiu, Y., Qiao, J., & Pardalos, P. M. (2019). Optimal production, replenishment, delivery, routing, and inventory management policies for products with perishable inventory. *Omega*, *82*, 193–204. DOI: 10.1016/j.omega.2018.01.006.

Rao, R. V., Savsani, V. J., & Vakharia, D. P. (2011). Teaching–learning-based optimization: a novel method for constrained mechanical design optimization problems. *Computer-aided design*, *43*(3), 303–315. DOI: 10.1016/j.cad.2010.12.015.

Saedi, S., Kundakcioglu, O. E., & Henry, A. C. (2016). Mitigating the impact of drug shortages for a healthcare facility: An inventory management approach. *European Journal of Operational Research*, *251*(1), 107-123. DOI: 10.1016/j.ejor.2015.11.017.

Scott, N. A., Lee, K. K., Sadowski, C., Kurbatova, E. V., Goldberg, S. V., Nsubuga, P., ... & Tuberculosis Trials Consortium. (2021). Optimizing drug inventory management with a web-based information system: The TBTC Study 31/ACTG A5349 experience. *Contemporary clinical trials*, *105*, 106377. DOI: 10.1016/j.cct.2021.106377.

Shiau, J. Y. (2019). A drug association-based inventory control system for ambulatory care. *Journal of Information and Optimization Sciences*, *40*(6), 1351-1365. *DOI: 10.1080/02522667.2019.1649032.*

Wacker, J. G. (1998). A definition of theory: research guidelines for different theory-building research methods in operations management. *Journal of Operations Management*, *16*(4), 361–385. DOI: 10.1016/S0272-6963(98)00019–9.

Wild, T. (2017). Best practice in inventory management. Routledge. *DOI: 10.4324/9781315231532.*

Wu, D., Wang, S., Liu, Q., Abualigah, L., & Jia, H. (2022). An Improved Teaching-Learning-Based Optimization Algorithm with Reinforcement Learning Strategy for Solving Optimization Problems. *Computational Intelligence and Neuroscience*, *2022*(1), 1535957. DOI: 10.1155/2022/1535957.