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A Genetic algorithm approach for improving the probabilistic inventory model with the continuous review: A practical application in the department of pharmacy

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Abstract:

This study investigates to shed light on artificial intelligence techniques, specifically the genetic algorithm, to improving traditional solutions, as well as finding the best policy for the problem of probabilistic inventory with continuous review by finding the optimal reorder point and the optimal economic quantity to avoid the risk of stock out (shortage), reduce total costs, and reach the optimal solution with little time and effort. The research was conducted in the stores of the department of pharmacy of the Ninawa health department for the period from January 1, 2021, to January 1, 2023, on a sample of three drugs (most demanded drugs). An analysis of the demand data for the study sample was conducted using the statistical program (SPSS Statistics Version 22) to determine the type of inventory. it was found that the type of inventory is probabilistic and the demand data follows a normal distribution. Based on this foundation, the mathematical model for the study problem was built. Given the complexity of the steps and iterations of the traditional solution, the solution steps were applied using the R programming language to reach the model's solution. Additionally, the solution steps were programmed for the genetic algorithm and applied using the R programming language. The results of the genetic algorithm showed an improvement in the traditional solution results by reducing total costs. Based on the results of the genetic algorithm, the economic order quantity, safety stock, reorder period, and safety period were found.

Paper type: Research Paper

Keywords: Probabilistic inventory model, Reorder point, Safety stock, Continuous review, Total costs of inventory, Genetic algorithm.

1.Introduction:

The evolution and progress in the field of technology, electronic computing, and data processing techniques have assisted researchers in various fields in accomplishing all the required studies and analyses for their research at a rapid pace. This progress has led to the emergence of artificial intelligence techniques and advanced evolutionary algorithms such as genetic algorithms. These algorithms aim to solve problems, overcome challenges, and quickly reach optimal solutions with minimal effort. Many institutions strive to implement these advanced technologies in various fields to enhance solutions, services, organize material storage operations, and increase profits. One of the most important areas is inventory control management (Atol et al., 2021).

The function of inventory is considered one of the most crucial functions adopted by institutions and companies, whether they are private or government entities. Improving the inventory system is a priority for these institutions. Regarding the healthcare sector, including pharmaceuticals and medical supplies, managing drug inventory has become critically important. Inadequate drug supplies and poor storage management and usage can impact human lives and result in financial and humanitarian losses. Therefore, developing and improving the inventory system in this sector is a priority and a focus of management attention (Masoudi and Mirzazadeh, 2022).

1.1 Literature review:

Given the importance of inventory models, several researchers have conducted different studies, including:

Jasim and Khalaf (2016) conducted a study on the optimal strategy for inventory control and using the fuzzy set theory in Baghdad Soft Drinks Production Company, this study aims to determine the economic quantities of production and demand for pepsi (330 ml). In addition to its basic components in the company, in an environment of uncertainty and fluctuation of demand quantities and costs associated with storage, as the foggy time series method was used in order to get rid of the uncertainty and fluctuation associated with requests for the final product, the fuzzy inference method was also used to remove the confusion and uncertainties associated with the costs of maintaining storage for the final product. The final results deduced the importance and efficiency of the use of the fuzzy theory by controlling the level of demand as well as the cost of maintaining storage, as well as the importance of using the productive storage model without deficit and its effectiveness in the process of determining the optimal economic quantity of production and demand.

Al-Bayati and Hamadi (2017) presented a genetic algorithm study to solve the problem of controlling multiple productive inventory based on the deterministic inventory models of the production companies in the event of with shortage as well as the without shortage for some of the products of the Middle Refineries Company most demanded in the local markets, the study included the use of traditional methods in the process of extracting the optimal economic quantities and the total costs of inventory. In order to improve the results, the genetic algorithm was used on the results obtained from traditional methods, and the results obtained showed that the use of the genetic algorithm reduced the shortage in the production process against the demand of materials and also contributed to reducing the total costs of inventory and for all the company's products by 26.15%.

Mubiru (2018) conducted a study on the problem of joint replenishment in the process of managing the drug inventory of pharmacies under random demand, and a mathematical model was proposed through which the inventory replenishment policies of the inventory system with periodic review are improved under the random demand, and the Markov decision approach was adopted in the decision-making process, which is represented by the cases of Markov chains and the demand for drugs that treat malaria are probabilistic.

Discrete Markov time series were used as well as programming dynamic and at limited horizon intervals, empirical data were collected and the data were analyzed and tested to determine the optimal policies and inventory costs. From the results reached, an optimal replenishment policy is based on the costs and status of the drug inventory.

Huang et al. (2021) applied the medical supplies inventory model and based on deep learning and big data, the purpose of this study was to solve the problems of emergency inventory management to improve the structure and efficiency of inventory management. An inventory management model for medical materials, which is based on deep learning and through reasonable classification of materials management methods, was created, and the results obtained to the proposed model can interpret and analyze the data well in addition to calculating inventory optimal and management method for the model with limited funds based on available data. Compared to the latest inventory management models, the proposed model can provide a forecast accuracy of up to 92.45 % and for the same data.

Shokouhifar et al. (2022) aimed to improve the problem of inventory management for the blood supply chain under uncertainty in supply and uncertain demand, in this study a model of inventory management was developed to reduce costs as well as both shortage and damage along the blood chain and according to its validity. The researchers used an algorithm to solve the model, taking into account the costs obtained on demand, transportation from blood centers, shortage, damage and inventory reservation. He used a case study of the blood supply chain to demonstrate the capacity and ability of the model to validate the proposed methodology. The researchers showed that the uncertainty in supply and demand, in addition to the limited validity of the blood, leads to significant damage to the total blood collected by donors. Conversely, there can be a large shortage in blood demand due to limited donor numbers and emergency requirements.

Amaya (2022) conducted a study on the application of the use of deep learning to improve the accuracy of the inventory model, in this study the researcher revisited the problems of traditional inventory management by checking whether deep learning algorithms provide an improvement on the established methods or not. He explored the application of deep learning as a means of identifying and correcting influential inventory log errors that can influence decisions about future reordering through take advantage of product levels, store levels, and inventory quality data. A trial was conducted on (450) supermarkets, leading grocery stores, and the results obtained showed that a decision model based on deep learning can provide significant improvement.

Liu et al. (2022) improved the management structure of medical inventory in the emergency department using artificial intelligence techniques. The existing management structure used to control inventory is not sufficiently effective and it is incompetent to solve the problems of medical supply inventory control. Therefore, deep learning and big data technology are employed in this study to improve the inventory control structure and enhance management efficiency, the stacked auto-encoders (SAE) algorithm was used to build the demand forecast model for MSI. Then, a simulation experiment compares the SAE-based demand prediction model for MSI with a back propagation neural network (BPNN) model and radial basis function network (RBFN) model to verify the model's performance. The experimental results demonstrate that after 150 times of training, the error between the predicted value and the actual value of each model is within 30, and the prediction accuracy is significantly improved. After 170 times of network training, the mean absolute error (MAE) values of BPNN model and RBFN model are 31.98 and 73.73, respectively. In contrast, the MAE value of the SAE-based model is 21.32, which is superior to the other two models. Finally, the results of this research have provided the most essential logistical support to deal with emergencies.

Asih et al. (2023) addressed order planning challenges related to perishable products, using bread products as a case study. The problem is how to efficiently manage the various bread products ordered by diverse customers, which requires distributors to determine the optimal number of products to order from suppliers. This study aimed to formulate the problem as a lot-sizing model, considering various factors, including customer demand, inventory constraints, ordering capacity, return rate, and defect rate, to achieve a near or optimal solution. Therefore, determining the optimal order quantity to reduce the total ordering cost becomes a challenge in this study. However, most lot sizing problems are combinatorial and difficult to solve. Thus, this study used the genetic algorithm (GA) as the main method to solve the lot sizing model and determine the optimal number of bread products to order. With (GA), experiments have been conducted by combining the values of population, crossover, mutation, and generation parameters to maximize the feasibility value that represents the minimal total cost. The results obtained from the application of GA demonstrate its effectiveness in generating near or optimal solutions while also showing fast computational performance. By utilizing GA, distributors can effectively minimize wastage arising from expired or perishable products while simultaneously meeting customer demand more efficiently.

Narang and De. (2023) studied an imperfect production inventory system with advertisement, price, and time-dependent demand for a non-instantaneous deteriorating item. Every manufacturing company aims to produce only perfect quality items, but this is not possible in reality. Firstly, the manufacturing system starts producing perfect items, but after some time, it starts producing imperfect items also, because of the manufacturing machine's long run. Perfect products are ready to sell, and some percentages of imperfect products are reworked to become perfect, and the remaining defective products are sold at a cheaper price. An efficiency cost is included to maintain the system efficiency. Considering these conditions, then they developed the profit function. This profit function is highly nonlinear. Therefore, a real coded genetic algorithm (GA) was used to obtain the optimal values of the production rate, selling price of the perfect quality item, selling price of imperfect item, and inverse efficiency factor to maximize the profit. Finally, the model is demonstrated by using numerical example followed by sensitivity analysis.

Tan et al. (2024) presented a study on an efficient inventory management model utilizing a multi-objective grey wolf optimization (MOGWO) method under stochastic demand. The multiple goals were to maximize profit and minimize the required storage space. The study aimed to determine the optimal order quantity for each product and the reorder point to optimize objective functions with constraints. The developed model is a nonlinear programming model mixed with binary variables, and optimization algorithms are realized to solve the inventory management problem. Sensitivity analysis was performed to further verify the optimal solutions, proving the robustness of the proposed algorithm and providing insight into how decision variables affect the optimal solutions. As the main contribution, the system introduced a new paradigm for solving inventory problems by optimizing multi-objective problems involving profit and storage space. From the test results it is shown that the MOGWO algorithm can deal with inventory problems with a significant difference in the range of values in objective functions. The study provided extensive numerical tests, and sensitivity analysis was applied to verify the optimal solutions under random demand. The study demonstrated that implementing the MOGWO algorithm significantly improves inventory management efficiency and therefore multi-objective optimization techniques can effectively assist managers in complex decision-making processes.

This study looks to shed light on artificial intelligence techniques, specifically genetic algorithm, in improving traditional solutions, and reaching the optimal solution in a quick time and little effort.

The problem of this study is to reduce the barriers and obstacles that occur in the process of storing and preparing drugs and medical supplies to the pharmacy department and review inventory levels on a continuous basis to avoid running out of stock and the occurrence of shortages that may affect people's lives.

The aim of this study is to provide the best inventory policy for the research sample by finding the optimal reorder point R^* and the quantity to be ordered by the department management to enhance the inventory (Economic order quantity Y^*) and based on the results of (R^*, Y^*) , the safety stock (ss), reorder period (rp) and the safety period (sp) are found. The importance of this study lies in achieving a balance between inventory costs, meeting demands for drugs, and avoiding the risks of stock outs (shortage) by following a policy of continuous review of inventory levels and finding the optimal strategy for inventory management.

2. Materials and Methods:

We will address the Inventory models in general and the continuous review model of the level inventory with probabilistic demand in detail, which includes several assumptions that were achieved in the data of the study sample and in the work policy of the pharmacy department's stores and also the genetic algorithm used to solve the mathematical model of the study will be addressed.

2.1 Inventory Models:

Inventory models have gone through several stages since their inception in 1913 by the scientist Harris, where the models were in their beginnings very simple and used a number of limited variables to understand the main factors. After that, the models increased in complexity by using many variables and in the fifties gradually probabilistic models appeared in which the demand is probabilistic and its quantity is unknown, as it is processed according to probability theory (Albazaz and Ibrahim, 2022).

The concept of inventory can be defined as the quantities held by the institution of all resources, including financial balances, human resources, and various needs of machinery, equipment, energy sources and other resources for the purpose of facing future conditions and needs (Hussin, 2019).

2.1.1 Some Economical Concept Related to Build an Inventory Model:

1- Order Quantity: When the inventory reaches a certain level (Reorder level), the management of the institution issues a purchase order for the stored material so that it is added to the available stock in order to increase its level, and the quantity added to the previous storage is called order quantity (Hassan et al., 2013).

2- Reorder Point (R): It is the minimum that the level of inventory may reach and then a purchase or production order is issued by the institution (Al-Shamarti, 2010).

3- Safety Stock (ss): It is a quantity of reserve stock that is kept to protect against unforeseen fluctuations and emergency conditions in orders, and it can be explained through the mathematical equation (1) (Hillier and Lieberman, 2015):

$$ss = R - E(x) \quad (1)$$

4- Holding Cost (h): It is the cost of keeping one unit for each Inventory cycle and includes the cost of place, insurance cost, examination and inspection cost (Abdul razaq and Naif, 2013).

5- Setup Cost (k): It is the cost of preparing the order or preparing the machines for each order, as it is calculated for each order and begins with the issuance of the purchase or production order and ends with the arrival of the materials to the stored. It includes costs issuing documents, transporting, unloading materials and arranging them in stores, communications, employee salaries and other administrative costs (Jasim and Khalaf, 2016).

6- Shortage Cost (p): It is the represents the cost of loss that the company or institution will incur will incur due to not having inventory when it is needed, as well as the bad impact on the company's reputation (Taha, 2018).

2.1.2 Inventory Models Classification:

Inventory models are classified according to the nature of the demand, which is either deterministic or probabilistic, if the demand is known constant with time determined with certainty (the rate of demand is fixed from one period to another), they are called (deterministic inventory models), the demand is rarely deterministic and known in advance in our daily lives. But if the demand is indefinite and probabilistic (the demand rate is probabilistic and variable from one period to another), it is called (probabilistic inventory models) and these models are either for a single period or for multi-period. There are two types basic systems for reviewing inventory levels to compensate for inventory, which are the continuous review system and the periodic review system. The classification can be clarified in figure (1) and the classification is similar if the system consists of a single-item or multi-item (Taha, 2018).

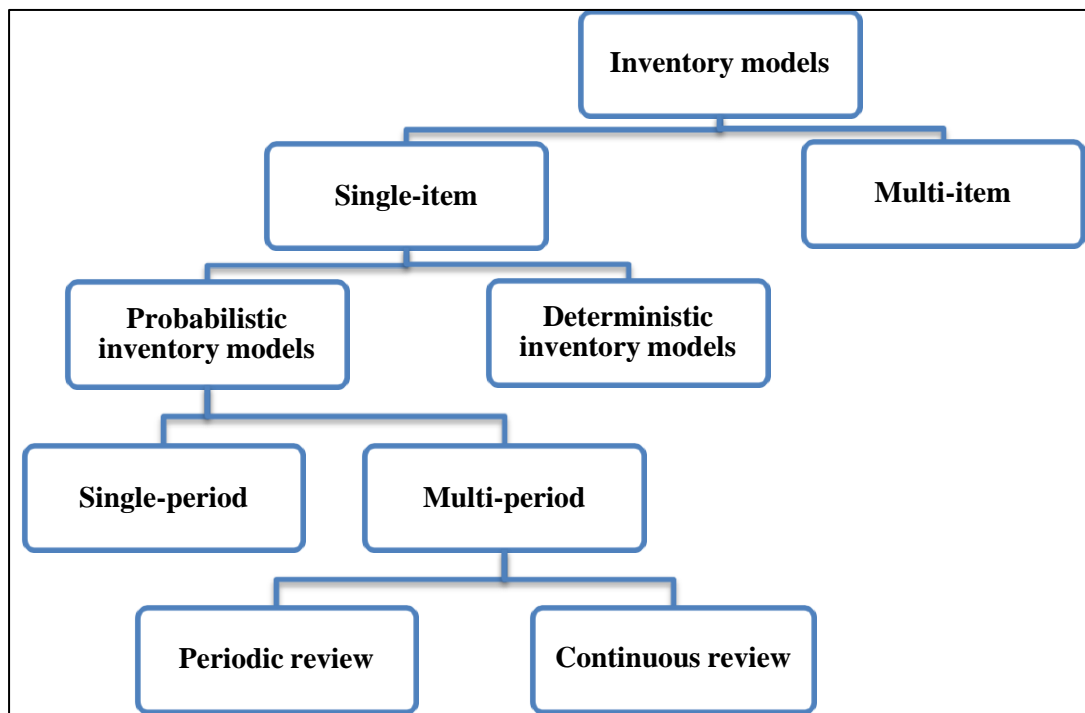


Figure 1: Inventory models classification. (Taha, 2018).

2.1.3 Determination of Data Fitting Inventory Model :

To determine the type of Inventory model, if it is deterministic or probabilistic, it is necessary to know the type and behavior of the demand. Assuming that we have demands $(d_1, d_2, d_3, \dots, d_n)$ for (n) time periods, to determine the type and behavior of the demand we must follow the following steps: (Taha, 2018).

1- Find the demand rate \bar{d} (Mean) for the known time period from the mathematical equation (2):

$$\bar{d} = \frac{\sum_{i=1}^n d_i}{n} \quad (2)$$

2- Find the standard deviation of demand for the known time period.

$$\sigma_D = \sqrt{\frac{1}{n} \sum_{i=1}^n d_i^2 - \bar{d}^2} \quad (3)$$

3- Find the coefficient of variance (VC) for the demand, the coefficient of variance is considered a standard for measuring the spread or variation (dispersion) of demand data around the average. It can be calculated from the mathematical equation (4):

$$VC = \frac{\sigma_D}{\bar{d}} * 100 \quad (4)$$

If the coefficient of variance is ($VC < 20\%$), this means that the demand is deterministic, and therefore the appropriate inventory model for the problem will be one of the deterministic inventory models, depending on the nature and type of the problem. If the coefficient of variance ($VC > 20\%$) means that the demand is probabilistic, and therefore the appropriate storage model for the problem will be one of the probabilistic inventory models.

2.1.4 Mathematical Model:

It was used (Continuous review model of the level inventory with probabilistic demand), as the idea of this model is focused on the fact that the demand for inventory is probabilistic and that the inventory depends on the reorder point (R), whenever inventory reaches this point or quantity, a new quantity of size Y is demanded. The aim of this model is to achieve a balance between Inventory costs, Meet customers' demands for materials, and avoiding the risk of stock outs and shortages this is done by finding the optimal reorder point (R^*) and the optimal economic order quantity to enhance inventory (Y^*). The figure (2) shows the model: (Khan and Dey, 2018).

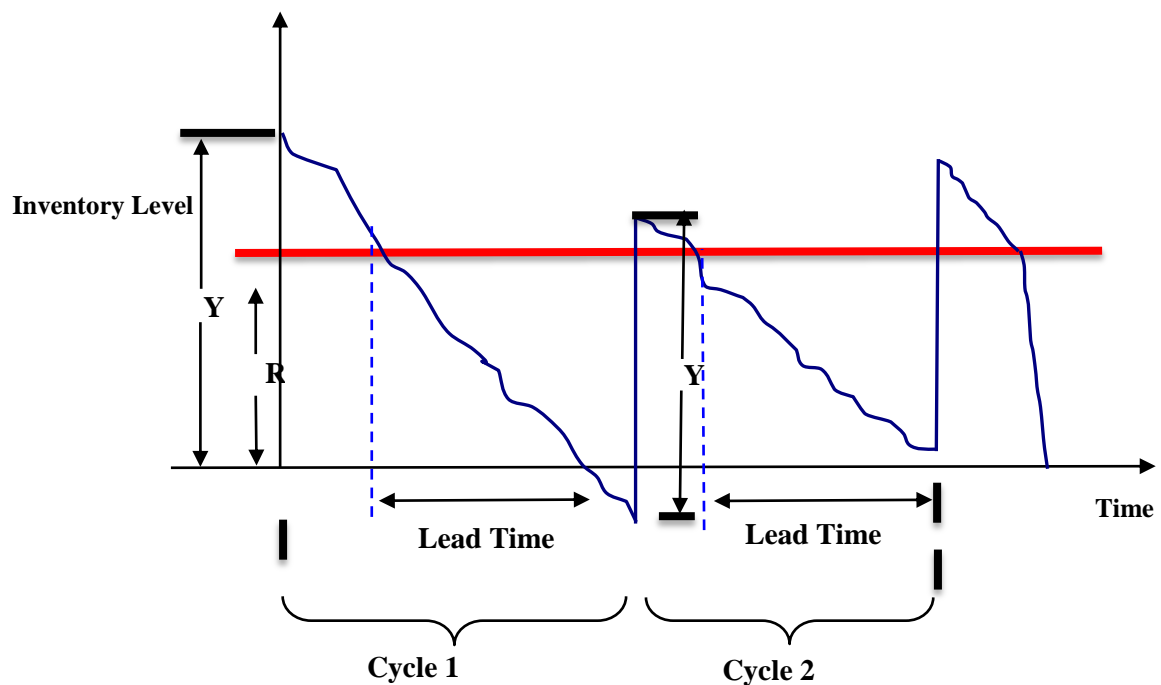


Figure 2: Continuous review model. (Khan and Dey, 2018).

Cycle is defined as the time period between the receiving of two demands. The assumptions of the model are: (Hillier and Lieberman, 2015).

- The inventory level is subject to continuous review so its current value is always known.
- Demand for inventory during the lead time is a probabilistic random variable with a known probability density function.

- Some demands that are not met from the inventory due to a shortage during the lead time are recorded in order to be fulfilled later once the material reaches the store.
- The time period between selecting the order and receiving it (lead time) is stochastic.
- The distribution of demand is independent of time during the lead time.
- The cost per unit (C) is fixed and independent of the size of the order (Y).
- The setup cost is fixed for each order issuance process.
- A certain holding cost is incurred, referred to as (h), the cost of holding inventory per unit and per period of time.
- When the inventory runs out, a cost is incurred, called the shortage cost (P) for each unit and for each period of time.

The (R, Y) policy is used, so the only decisions to be made are to choose (R^*) and (Y^*) .

Assuming symbols and variables for the model: (Hillier and Lieberman, 2015)

1-Reorder point (R), 2-Economic order quantity(Y), 3-Annual demand (D), 4-Setup cost (k), 5-Holding cost (h), 6-Shortage cost (p), 7-Expected shortage per cycle (\bar{S}), 8-Complementary cumulative distribution function (\bar{F}), 9-Order quantity during the lead time (x), 10-Expected demand $E(x)$, 11-Mean of the normal distribution (μ), 12-Standard deviation of the normal distribution (σ), 13-Unit size of item j (f_j), 14- Custom storage capacity of the item j (A_j), 15- Number of item (n), 16-Number of iteration (i), 17-Safety stock (ss), 18-Reorder period (rp), 19-Safety period (sp).

The total inventory cost equation is as follows (Abed Diab, 1986; Al-Shamarti, 2010):

$$TAC(Y, R) = k \frac{D}{Y} + h \left(\frac{Y}{2} + R - E(x) \right) + p \frac{\bar{S}}{Y} D \quad (5)$$

To obtain R^* and Y^* , we take the partial derivative of the mathematical equation (5), and then make it equal to zero in the following two cases:

$$\frac{\partial TAC}{\partial Y} = 0 \quad , \quad \frac{\partial TAC}{\partial R} = 0$$

$$Y^* = \sqrt{\frac{2D(k + p\bar{S})}{h}} \quad (6)$$

$$\int_R^{\infty} f(x)dx = \frac{hY^*}{pD} \quad (7)$$

It is not possible from the above equations to calculate the numerical value of (R^*) and (Y^*) , but there is a numerical method to solve the two equations and their steps as follows:

In equation (2) when there is no shortage and (\bar{S}) is at least equal to zero, here (Y^*) appears in its lowest value, which is:

$$Y^* = \sqrt{\frac{2Dk}{h}} \quad (8)$$

This value is appropriate when $\bar{S} = 0$ or $(R \rightarrow \infty)$, we substitute in equation (6) with $R = 0$ and when there is a shortage

$$Y^* = \sqrt{\frac{2D(k + p\bar{S})}{h}} \quad (9)$$

Since the value of \bar{S} when $R = 0$ is:

$$\bar{S} = \int_0^{\infty} Xf(x)dx = E(x)$$

The optimal economic order quantity (Y^*) is as follows:

$$Y^* = \hat{Y} = \sqrt{\frac{2D(k + pE(x))}{h}} \quad (10)$$

Also, equation (3) and when $R = 0$ is as follows

$$Y^* = \tilde{Y} = \frac{pD}{h} \quad (11)$$

The demand is probabilistic, and for the purpose of processing it must be used probability theory. In this study, the probability distribution of the demand is (Normal distribution), whose average is (μ), its standard deviation is (σ), and the probability density function is:

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2} dx \quad (12)$$

and to find the integration of the normal distribution function after entering it in the inventory model:

$$\begin{aligned} \bar{S} &= \int_R^{\infty} (X - R) \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2} dx \\ \bar{S} &= \sigma f\left(\frac{R - \mu}{\sigma}\right) + (\mu - R)\bar{F}\left(\frac{R - \mu}{\sigma}\right) \end{aligned} \quad (13)$$

2.2 Artificial Intelligence Algorithms:

Algorithms are a series of arithmetic operations and steps that transform inputs into mathematical outputs and deal with problems whose solutions are located in large-dimensional space for the purpose of shortening the road and reaching the optimal solution without going through all the solutions within the solution space, so that the algorithm starts with one solution, evaluates and improves it until a solution that meets the required conditions and the imposed restriction (Mirjalili, 2019).

Currently, there is a variety of algorithms for most problem types, however, there are different cases of the same problem that may require different arithmetic requirements, this has given way to the development of new algorithms and as a result there will be a continuous need for new and sophisticated ideas in optimization theory and its applications. Over the past two decades, the most recent development is the tendency to use metaheuristic algorithms, and these algorithms have become very powerful and useful in solving complex optimization problems. Metaheuristic algorithms can be classified into path-based or individual-based and community-based algorithms such as genetic algorithm (Yassin et al., 2019).

2.2.1 The Concept of Genetic Algorithm:

It is considered one of the most important types of algorithms in artificial intelligence for the process of improving competing solutions, as it is a random improvement technique inspired by the process of natural selection, based on the principle of survival of the fittest, and is widely applied to solve various problems and in many fields, (Scrucca, 2013). This flexibility has made it attractive to many improvement problems in the practice of evolution, which is the basis of a genetic algorithm (Han et al., 2021).

The idea of the genetic algorithm is to create and generate some solutions to the problem randomly and then the process of examining these solutions and comparing them with some criteria designed by the algorithm designer, and the best solutions are the remaining ones. As for the less effective and efficient solutions, they are neglected according to the biological rule (survival of the fittest), and then the remaining solutions (the most efficient) are combined to produce new solutions similar to what happens in living organisms by mixing their genes, as the new organism's characteristics will be a mixture of the characteristics of its parents, and that these solutions resulting from the crossover process are subject to examination and refinement to know their efficiency and proximity to the optimal solution. Thus, crossover and selection processes are carried out until a certain number of iterations is reached, which is estimated by the algorithm designer, or until the resulting solutions, or one of them, reaches a high efficiency ratio (Salem et al., 2003).

2.2.2 Rules Base Application Genetic Algorithm:

The basic rules in applying the genetic algorithm can be summarized in the following steps and stages: (Baluja and Caruana, 1995; Mirjalili, 2019).

1. Initialization.
2. Selection.
3. Reproduction.
4. Crossover.
5. Mutation.

Figure (3) shows the stages of applying the genetic algorithm: (Ibrahim and Jabr, 2022; Wu et al., 2021; Rao, 2019;).

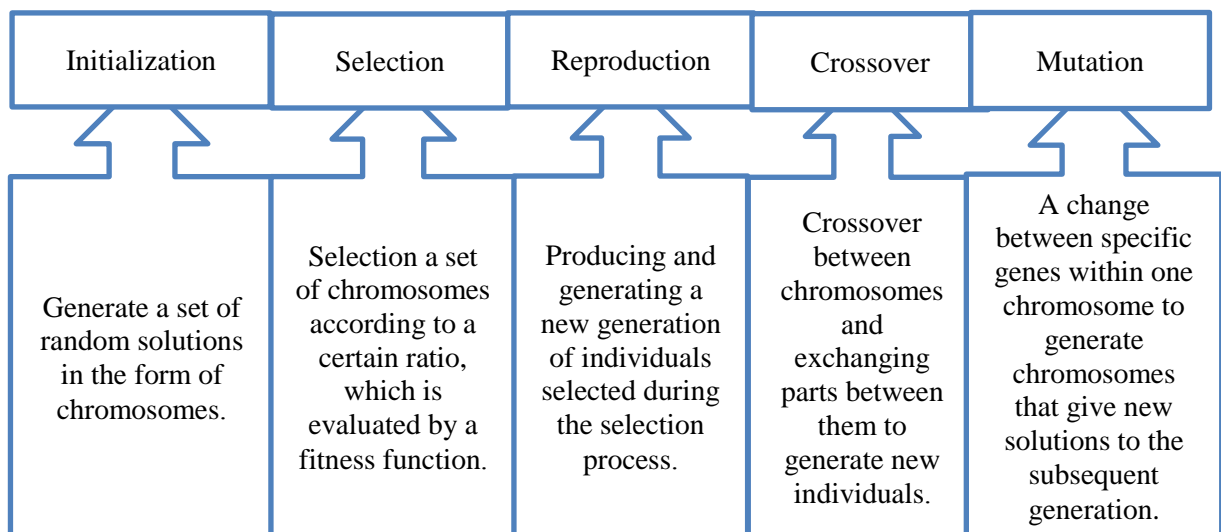


Figure 3: Rules base application genetic algorithm. (Ibrahim and Jabr, 2022; Wu et al., 2021; Rao, 2019).

Termination conditions the previous operations continue to be repeated until the optimal solution is reached or the number of generations or a certain value is found after achieving the required conditions for the problem under study.

2.2.3 Basic Parameters of Genetic Algorithm:

There are four important and basic parameters used by genetic algorithm, those include: (Hassanat et al, 2019).

1- Population Size: The size of the population indicates the total number of the population or chromosomes in one generation. Selection of population size is a sensitive issue, if the size of the population (search space) is small, it leads to poor diversity this means little search space is available, and therefore it is possible to reach a local optimum. although, if the population size is very large, the area of search is increased and the computational load becomes high, therefore, the size of the population must be reasonable.

2- Crossover Rate: The number of times a crossover occurs for chromosomes in one generation and responsible for the generation of chromosomes for the next generation, i.e., the chance that two chromosomes exchange some of their parts), (100%) crossover rate means that all offspring are made by crossover. If it is (0%) then the complete new generation of individuals is to be exactly copied from the older population, except those resulted from the mutation process. Crossover rate is in the range of [0,1].

3- Mutation Rate: This rate determines how many chromosomes should be mutated in one generation; it is possible for the mutation to occur on all or half of the genes of the chromosomes, or not to occur on any of the genes. Mutation rate is in the range of [0, 1]. The purpose of mutation is to prevent the GA from converging to local optima, but if it occurs very often, GA is changed to random search.

4- Number of generations: It refers to the number of cycles or loops before the termination and conduct improvement operations until appropriate results are achieved. In some cases, hundreds of loops are sufficient, but in other cases we might need more, this depends on the problem type and complexity. Depending on the design of the GA, sometimes this parameter is not used, particularly if the termination of the GA depends on specific criteria.

2.2.4 Basic Features of the Genetic Algorithm :

The features and characteristics of the genetic algorithm can be summarized as follows: (Magalhaes, 2013; Hosseini and Kamalabadi, 2013).

1- The genetic algorithm is used to solve large problems with many variables.

2- The genetic algorithm shortens a lot of time and effort in solving problems, taking into account the privacy, restrictions and data of each problem. It is also considered more effective than traditional methods in solving optimal problems or problems that traditional (classical) methods are unable to solve and reach optimal solutions.

3- This algorithm is considered simple, uncomplicated and does not need additional conditions such as continuity and distinction between objective functions and derivatives of the function under study.

4- The initial population solutions are generated and produced randomly, some genetic algorithms use other exploratory methods to generate initial population solutions to the problem under study, and then the solutions are evaluated until the optimal solution is reached.

5- A genetic algorithm uses many possible solutions so it usually avoids local optimal solutions.

3. Discussion of Results:

3.1 Collecting Data Related to Inventory Model:

Data related to the research problem was collected through digital records and statistics recorded in the stores of the pharmacy department of the Nineveh Health Department, as well as through personal interviews with department employees, divisions, and store keepers in the department, and learning about the workflow mechanism. The stores of the pharmacy department receive drugs from the Ministry of Health, as they are saved, arranged and inventoried, and storage supplies are provided such as cooling, heating and other logistical matters so that they can then distribute them to health institutions in Nineveh Governorate and according to need. The research sample consists of three drugs (most demanded drugs) by health institutions, which are (Amoxicillin 500mg - Sodium chloride 0.9%, 500ml - Antipyrol syr 100 ML) as the demand data was collected for the research sample and for the time period from (2021-1-1) until (2022-12-31).

3.2 Test Data:

The necessary statistical analyzes were conducted to determine the type of inventory model for the research sample, according to the steps previously mentioned in paragraph (2.1.3), using equations (2) to find the average, equation (3) to find the standard deviation, and equation (4) to find the coefficient of variation, and using the program (Microsoft Office 2016 – Excel), the results shown in Table (1) were obtained:

Table 1: Statistical analyzes of demand data by using (Microsoft office 2016 – Excel)

No.	Item	D	Min	Max	Mean	Standard Deviation	VC.
1	Amoxicillin	1281284	32760	74030	53387	13071	24.48 %
2	Sodium chloride	1121190	31925	65250	46716	9979	21.36 %
3	Antipyrol	1594808	41660	96835	66450	17703	26.64 %

We notice from the results of the table (1) that the coefficient of variation for all drugs is greater than (20%). This means that the inventory model is probabilistic.

After identifying the type of inventory model for the study in the previous paragraph that it is a probabilistic inventory model, now, it must be known that the demand data available to the study sample is distributed normally or not, the statistical system was used (SPSS Statistics Version 22) and through the use of the (Kolmogorov-Smirnov Test) for normal distribution and according to the following hypothesis:

H_0 : Null Hypothesis (Data are normally distributed).

H_1 : Alternative Hypothesis (Data are not normally distributed).

if the significance level is ($Sig > 0.05$), the null hypothesis (H_0) is accepted and the alternative hypothesis (H_1) is rejected, this means that the data is distributed normally. However, if the significance level is ($Sig < 0.05$), the null hypothesis (H_0) will be rejected and the alternative hypothesis (H_1) will be accepted, this means that the data is not normally distributed. The table (2) shows the test results:

Table 2: Kolmogorov-Smirnov test for demand data by using the ready-made software (SPSS Statistics Version 22)

Type		Amoxicillin	Sodium chloride	Antipyrol
N		24	24	24
Normal Parameters ^{a,b}	Mean (μ)	53387	46716	66450
	Std. Deviation	13071	9979	17703
Most Extreme Differences	Absolute	.163	.116	.166
	Positive	.135	.116	.166
	Negative	-.163	-.092	-.116
Test Statistic		.163	.116	.166
Asymp. Sig. (2-tailed)		.101 ^c	.200 ^{c,d}	.087 ^c

We note from the table (2) that the value of the level of significance for all items is (Sig > 0.05), This means that the demand data is distributed normally.

3.3 Data used in Solving the Inventory Model for the Study Sample :

The setup cost for each order is (190,000 ID), and the table (3) shows the rest of the data used in solving the probabilistic inventory model.

Table 3: Data used in solving the inventory model

No.	Item	h ID	p ID	f_j M ³	A_j M ³
1	Amoxicillin	3.655	5.942	0.00004	20.00000
2	Sodium chloride	4.182	6.790	0.00135	540.00000
3	Antipyrol	2.831	4.774	0.00070	399.00000

3.4 Solving the Mathematical Model for Inventory:

The optimal reorder point (R^*) and the optimal economic order quantity (Y^*) in the probabilistic inventory model with continuous review reduce or decrease the overall expectation of inventory cost per unit time. Due to the difficulty of applying the solution steps and iterations, the solution was prepared using the (R-programming language), where the optimal reorder point and the optimal Economic order quantity to enhance the inventory were calculated based on the equations of the probabilistic inventory model with continuous review that was mentioned previously, and the total cost was calculated in light of the results (R^* , Y^*).

3.4.1 Calculate R^* and Y^* in the Traditional (Classical) Method:

Find the values of (R^*) and (Y^*) according to the following steps:

✓Step 1: Perform the basic test between the value of (\tilde{Y}) resulting from equation (11), and the value of (\hat{Y}) from equation (10), when $(\tilde{Y} \geq \hat{Y})$.

This means that there are optimal values for (R^*) and (Y^*) and we go to the next step. Otherwise, it means that there are no optimal values for (R^*) and (Y^*)

✓Step 2: Find (Y_i) using equation (8).

✓Step 3: Finding (R_i) based on the value of (Y_i) and through the equation (7), and we find the basic value corresponding to $\frac{hY}{PD}$ and replace it in the equation $(\frac{R-\mu}{\sigma})$.

✓Step 4: Find (\bar{S}) using equation (13).

✓Step 5: Find (Y_{i+1}) using equation (6).

✓Step 6: Find (R_{i+1}) using equation (7) based on the value of (Y_{i+1}) .

✓Step 7: We continue with steps (4-5-6) until we obtain a value of (R_{i+1}) equal to or close to the value of (R_i) , so we stop at these values, and then the value of (R^*) and (Y^*) are the optimal values.

After applying the above steps to the research sample and using the (R-programming language), the results shown in table (4) were reached:

Table 4: Results of solving the traditional method by using the (R-programming language)

No.	Item	Optimal Reorder Point (R^*)	Optimal Economic Order Quantity (Y^*)	Expected shortage (\bar{S})	Required Storage Capacity M^3
1	Amoxicillin	65419	372126	1264	17.50180
2	Sodium chloride	55914	324628	963	513.73170
3	Antipyrol	82952	472314	1675	388.68620

From the results of table (4), we note that when the inventory level of Amoxicillin reaches the level of the optimal reorder point, which is (65419) units, decision makers must demand the optimal economic quantity for demand, which is (372126) units, and the expected shortage will then be (1264) units. As for Sodium chloride, when the inventory level reaches (55914) units, decision makers must demand the optimal economic quantity for demand, which is (324628) units, and the expected shortage will be (963) units. As for Antipyrol, when the inventory level reaches (82952) units. Decision makers must demand the optimal economic quantity of demand, which is (472314) units, and the expected shortage will be (1675) units. We also note that the storage capacity that the materials need to store is less than the allocated storage capacity, and this means that the size allocated for each material is sufficient and appropriate for it.

3.4.2 Calculate the Total Costs of Inventory by Traditional (Classical) Method:

After calculating the optimal reorder point and the optimal economic quantity of demand for the materials of the study sample and in light of their results, the total cost of inventory is found through equation (5) and using the program (R-programming language). The table (5) shows the total costs extracted for the materials:

Table 5: Total cost results using the traditional (classical) method

No.	Item	Total Cost $TAC(R^*, Y^*)$
1	Amoxicillin	1,404,098.28 ID
2	Sodium chloride	1,396,060.62 ID
3	Antipyrol	1,383,838.32 ID
4	Total	4,183,997.22 ID

From the results of table (5), the total inventory cost for the substance (Amoxicillin) was (1,404,098.28) ID, which is the highest cost compared to the rest of the materials in the study sample. As for Sodium chloride, the total inventory cost for it amounted to (1,396,060.62) ID, and the total inventory cost for the substance (Antipyrol) is (1,383,838.32) ID and is the lowest cost compared to the rest of the materials in the study sample. The total cost of all materials was (4,183,997.22) ID.

3.4.3 Calculate the R^* and Y^* by using Genetic Algorithm:

The steps for solving the genetic algorithm were prepared on the R-programming language to calculate the reorder point, the economic order quantity, and the total inventory cost. The type of optimization: (Min) was determined for the total cost, which is considered a function (Fitness Function), the chromosome encoding method used is (real value encoding), the number of generations is (MaxIter = 1000), the number of solutions in each generation (NumPopulation=400), the range of variable values for the mutation rate and the crossover rate is (rangeVar, Pm = 0.1, Pc = 0.8). After writing the steps of the program, it was executed and the results shown in table (6) were reached:

Table 6: Results of solving the genetic algorithm by using the (R programming language).

No.	Item	Optimal Reorder Point (R^*)	Optimal Economic Order Quantity (Y^*)	Expected shortage (\bar{S})	Required Storage Capacity M^3
1	Amoxicillin	64559	372261	1140	17.4728
2	Sodium chloride	55146	324770	840	512.8866
3	Antipyrol	82013	472289	1548	388.01140

From the results of table (6), the best strategy was found to control the inventory of the study sample materials, which must be followed by the management and decision makers in the store. When the inventory level of the substance (Amoxicillin) reaches the level of the optimal reorder point, which is (64559) units, the decision makers must request the optimal economic quantity for demand, which is (372261) units, and the expected shortage will be the little as possible, which is (1140) units. As for Sodium chloride, when the inventory level reaches (55146) units, decision makers must request the optimal economic quantity for demand, which is (324770). units, and the expected shortage will be the little as possible, which is (840) units. As for the substance (Antipyrol), when the inventory level reaches (82013) units, decision makers must request the optimal economic quantity for demand, which is (472289) units, and the expected shortage will be (1548) units. It also turns out that the storage capacity needed for the materials in the store is less than the allocated storage capacity. This means that the storage capacity allocated for each material is sufficient and appropriate for it.

3.4.4 Calculate the Total Costs of Inventory by using Genetic Algorithm:

The total inventory cost of materials was calculated using a genetic algorithm based on the results of (R^*, Y^*) and for each material separately, and the results were obtained in the table (7):

Table 7: Total Cost results using the genetic algorithm

No.	Item	Total Cost $TAC(R^*, Y^*)$
1	Amoxicillin	1,398,416.05 ID
2	Sodium chloride	1,389,967.75 ID
3	Antipyrol	1,379,123.69 ID
4	Total	4,167,507.49 ID

The total cost of inventory for Amoxicillin was (1,398,416.05) ID, while for Sodium chloride, the total cost was (1,389,967.75) ID, and the total cost for Antipyrol was (1,379,123.69) ID. The total cost of all materials amounted to (4,167,507.49) ID.

3.4.5 The Difference between the Results of the Traditional Method and the Genetic Algorithm:

After the solution was found in the traditional way and also using the genetic algorithm, it was found that the genetic algorithm reduced the total costs of inventory for all materials in the study sample. The table (8) shows the difference between the total costs of inventory in the traditional way and using the genetic algorithm:

Table 8: The difference between the results of the traditional method and the genetic algorithm in calculating the total inventory cost

No.	Item	Total Cost (Classical) $TAC(Y, R)$	Total Cost (GA.) $TAC(Y, R)$	The difference between the two methods
1	Amoxicillin	1,404,098.28 ID	1,398,416.05 ID	-5,682.23 ID
2	Sodium chloride	1,396,060.62 ID	1,389,967.75 ID	-6,092.87 ID
3	Antipyrol	1,383,838.32 ID	1,379,123.69 ID	-4,714.63 ID
4	Total	4,183,997.22 ID	4,167,507.49 ID	-16,489.73 ID

The total cost of inventory the material (Amoxicillin) using the traditional method was (1,404,098.28) ID, while using the genetic algorithm it amounted to (1,398,416.05) ID, meaning that the genetic algorithm reduced the total costs of the material by an amount of (5,682.23) ID. The total cost of inventory the material (Sodium chloride) using the traditional method was (1,396,060.62) ID, and using the genetic algorithm it amounted to (1,389,967.75) ID, meaning that the genetic algorithm reduced the total cost of the material by an amount of (6,092.87) ID. The total cost of inventory the material (Antipyrol) using the traditional method was (1,383,838.32) ID, and using the genetic algorithm it amounted to (1,379,123.69) ID, meaning that the genetic algorithm reduced the total costs of the material by an amount of (4,714.63) ID. The total inventory costs for all study sample materials in the traditional method amounted to (4,183,997.22) ID, and using the genetic algorithm amounted to (4,167,507.49) ID, meaning that the genetic algorithm reduced the total inventory costs for all materials (research sample) by (16,489.73) ID.

3.4.6 Calculate the Safety Stock and Reorder Period:

In light of the results of the genetic algorithm for the values of the reorder point and the optimal economic quantity of demand (R^*, Y^*), the safety stock was calculated using mathematical equation (1) and the safety period was calculated by (dividing the safety stock ss by the demand Mean μ) and calculating reorder period by (dividing the optimal economic quantity by the demand Mean μ). Table (9) shows the results obtained:

Table 9: Results of solving safety stock and reorder period

No.	Item	ss	$\frac{sp}{\mu} * 30$	$\frac{rp}{\mu} * 30$
1	Amoxicillin	11172	6	209
2	Sodium chloride	8430	5	209
3	Antipyrol	15563	7	213

From the results of table (9), we note that the safety stock for Amoxicillin is (11,172) units, and on this basis, the safety period for reordering is (6) days before the stock quantities arrive on (209) days. Also, the safety stock of sodium chloride reached (8430) units, and on this basis, the safety period for reordering is (5) days before the stock quantities arrive on (209) days. As for the safety stock of Antipyrol, it reached (15563) units, and on this basis, the safety period for reordering is (7) days before the stock quantities arrive on (213) days.

4. Conclusions:

In this study, after identifying the problem of controlling inventory for the study sample in the Department of the Pharmacy and Medical Supplies of the Nineveh Health Department, conducting the necessary statistical analyses, building a mathematical model and solving it in the traditional way and using a genetic algorithm, a set of conclusions were reached, which can be summarized as follows:

- 1- The type of demand for materials in the research sample is probabilistic, and according to the Kolmogorov-Smirnov Test, it was found that it follows a normal distribution.
- 2- The best strategy has been found to control the inventory of Amoxicillin, as when the inventory level reaches the optimal reorder point of (64,559) units, the decision maker must issue an order to demand the amount of the optimal economic quantity, which is (372,261) units, and the amount of the safety stock is (11,172) units. Accordingly, it will be the safety period for reordering is (6) days before the inventory quantities arrive for day (209). The best strategy has also been found to control the inventory of sodium chloride. When the inventory level reaches the optimal reorder point of (55,146) units, the decision maker must issue an order to demand the amount of the optimal economic quantity, which is (324,770) units, and the amount of safety stock is (8430) units. Accordingly, it will be the safety period for reordering is (5) days before the inventory quantities arrive for day (209). The best strategy has been found to control the inventory of the Antipyrol, as when the inventory level reaches the optimal reorder point of (82,013) units, the decision maker must issue an order to demand the amount of the optimal economic quantity, which is (472,289) units, and the amount of the safety stock is (15,563) units. Accordingly, it will be the safety period for reordering is (7) days before the inventory quantities arrive for day (213).
- 3- Through the results of solving the model, it was found that the storage capacity required to store Amoxicillin, amounting to (17.4728) M^3 , is less than the storage capacity allocated by the Pharmacy Department management, amounting to (20.00000) M^3 . This means that the storage capacity restriction does not affect the optimal economic order quantity and the reorder point.

The storage capacity required to store Sodium chloride, amounting to $(512.8866) M^3$, is less than the storage capacity allocated by the pharmacy department management, which is $(540.00000) M^3$. This means that the storage capacity restriction does not affect the optimal economic order quantity and the reorder point. Also, the storage capacity required to store Antipyrol, amounting to $(388.01140) M^3$, is less than the storage capacity allocated by the pharmacy department management, which amounts to $(399.00000) M^3$. This means that the storage capacity restriction does not affect the optimal economic order quantity and the reorder point.

4- By solving the storage model in the traditional way and applying steps the solution using the program (R-programming language), the total cost of the study sample materials reached $(4,183,997.22)$ ID, and after using the genetic algorithm it amounted to $(4,167,507.49)$ ID, meaning that the genetic algorithm reduced the total storage costs and helped in achieving a balance between the storage costs and fulfilling demands by finding (R^*, Y^*) and makes the expected shortage will be the little as possible.

5- The genetic algorithm can be applied to solve the problem of controlling storage for the rest of the materials in the pharmacy department's stores, as the study sample was three drugs out of a total of (778) drugs, and thus, it is possible to find the best inventory policy for them that can be followed to fulfilling demands, avoid running out of inventory and the occurrence of a shortages that may affect human lives, and thus reduce overall costs.

6- Genetic algorithms can be used to solve optimization and improvement issues in operations research models, specifically the probabilistic inventory model with continuous review, to achieve the best results in a short time and with little effort.

Authors Declaration:

Conflicts of Interest: None

-We Hereby Confirm That All The Figures and Tables In The Manuscript Are Mine and Ours. Besides, The Figures and Images, Which are Not Mine, Have Been Permitted Republication and Attached to The Manuscript.

- Ethical Clearance: The Research Was Approved By The Local Ethical Committee in The University.

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تحسين نموذج الخزين الاحتمالي ذو المراجعة المستمرة باستعمال الخوارزمية الجينية مع التطبيق العملي في قسم الصيدلة

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هذا العمل مرخص تحت اتفاقية المشاع الإبداعي تُسبب المُصنّف - غير تجاري - الترخيص العمومي الدولي 4.0 Attribution-NonCommercial 4.0 International (CC BY-NC 4.0)



مستخلص البحث:

تبحث هذه الدراسة في تسليط الضوء على تقنيات الذكاء الاصطناعي وتحديدًا الخوارزمية الجينية في تحسين الحلول التقليدية وإيجاد أفضل سياسة لمشكلة المخزون الاحتمالي ذو المراجعة المستمرة من خلال إيجاد نقطة إعادة الطلب المثلى والكمية الاقتصادية المثلى لتجنب مخاطر نفاذ المخزون (العجز) وبالتالي تقليل التكاليف الكلية والوصول إلى الحل الأمثل بوقت وجهد قليل. أجري البحث في مخازن قسم الصيدلة التابعة لدائرة صحة نينوى وللفترة 1 كانون الثاني 2021 إلى 1 كانون الثاني 2023 على عينة بلغت ثلاث أدوية (أكثر الأدوية طلباً). تم إجراء تحليل بيانات الطلب لعينة الدراسة باستخدام البرنامج الإحصائي (SPSS Statistics Version 22) لمعرفة نوع الخزين. وتبين أن نوع الخزين هو احتمالي وبيانات الطلب تتبع التوزيع الطبيعي. على هذا الأساس تم بناء النموذج الرياضي لمشكلة الدراسة. نظراً لتعقيد خطوات وتكرارات الحل التقليدي تم تطبيق خطوات الحل على برنامج (R-programming language) والتوصل إلى حل النموذج. كما تم برمجة خطوات الحل للخوارزمية الجينية وتطبيقها على (R-programming language). أظهرت نتائج الخوارزمية الجينية تحسناً في نتائج الحل التقليدي وذلك بتقليل التكاليف الكلية. وبناءً على نتائج الخوارزمية الجينية تم الكمية الاقتصادية المثلى ومخزون الأمان وفترة إعادة الطلب وفترة الأمان.

نوع البحث: ورقة بحثية .

المصطلحات الرئيسية للبحث: نموذج الخزين الاحتمالي. نقطة إعادة الطلب, مخزون الأمان, المراجعة المستمرة, التكاليف الاجمالية للخزين, الخوارزمية الجينية.