Pesquisa Operacional (2022) 42: e257747 p.1-26
doi: 10.1590/0101-7438.2022.042.00257447

Printed version ISSN 0101-7438 / Online version ISSN 1678-5142
www.scielo.br/pope
ARTICLES

AN EFFICIENT INVENTORY MODEL-BASED GA FOR FOOD DETERIORATION PRODUCTS IN THE TOURISM INDUSTRY

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Received October 18, 2021 / Accepted June 12, 2022

ABSTRACT. *Background:* The inventory control practice of deteriorating food products that are subject to an expiration date is a challenging process. Inappropriate inventory control practice leads to substantial waste of products and significant holding and purchasing costs. *Purpose:* This paper aims to develop an inventory control model-based Genetic Algorithm (GA) to minimize the Total Annual Inventory Cost (TAIC) function developed explicitly for the proposed model. *Methodology:* GA is used and tailored to provide the best reorder level of deteriorating food products. A case study of one of the five-star hotels in Iraq is conducted, followed by a sensitivity analysis study to validate the proposed model for varying reorder levels. *Results and Conclusion:* A minimum inventory cost is obtained with an optimum reorder level achieved by running GA. It is concluded that the optimal reorder level provided by the proposed GA minimized the monthly inventory cost of products.

Keywords: deteriorating food products, inventory control, genetic algorithms.

1 INTRODUCTION

Due to many factors, the deterioration of food products is a frequent, gradual, and natural phenomenon. These factors include inappropriate lighting, temperature, humidity, and spoilage bacteria that affect the quality and safety of such products, causing food spoilage and making their items out of validity in terms of human consumption. However, the main factor behind such food deterioration is that keeping an excessive quantity of food products than the possible consumption rate will drive the surplus products' age to go beyond their expiry date, resulting in their classification as spoiled products and their subsequent disposal.

In order to reduce storing an excessive quantity of food, a prediction of the food consumption rate needs to be conducted. In addition, the current storage of these products needs to be regularly

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checked to ensure that no additional products will be ordered/purchased. Therefore, inventory control practice is required as an essential process of monitoring and controlling the products' storage by proposing inventory control tools and techniques to achieve the best inventory control practice. This practice ensures the optimal balance between inventory levels of products and predicted consumption rate or volumes of products' demands. This reduces the waste of perishable foods and the costs related to their purchase and storage (Akhir et al., 2019). It is worth mentioning that the problem of food deterioration, whose expected usefulness ends when the product's shelf life reaches zero, was also discussed as an inventory control problem (Nahmias, 1982; Yadav et al., 2017; Yadav et al., 2018).

The deterioration of food products, including their volumes and types, causes waste and, subsequently, the high cost of holding and purchasing them. This issue could also lead to a lost opportunity cost when a particular food product is requested and not ready for delivery. Therefore, the cost analysis within the inventory control practice should be considered for an effective inventory control practice of food products.

Therefore, the main aim of this study is to develop an effective inventory control model-based genetic algorithm (GA) for achieving optimal reorder levels of food deteriorating products and minimizing the total inventory purchasing costs. The total purchasing cost function is proposed and added to the classical purchasing with no shortage inventory model for a more cost-effective analysis. A case study of the tourist industry represented by one of the five stars' hotels located in the North of Iraq is also considered in this study.

The benefits of this inventory control model are summarized as follows:

(i) It assists business operations managers in identifying the optimal level of inventory in response to the current consumption rate of food products.

(ii) It reduces waste of the deterioration of food products due to improper inventory storage policies.

(iii) It also contributes to minimizing costs associated with holding unnecessary volumes of food products and the incurred waste of storing a volume of food products higher than the actual demand requires.

The paper is organized as follows: Section II reviews the literature on inventory control modeling of food products considering their deterioration. The development of the inventory-GA model and a cost function of total purchasing of food products are discussed in Section III. Section IV presents a case study in one of Iraq's five-stars hotels. Section V presents a sensitivity analysis to study the reaction of the developed model to different demand scenarios, followed by the main conclusions and recommendations in the last section.

2 PROBLEM DESCRIPTION

Nowadays, most businesses, because of the high software purchasing costs, complications or wide range of software capabilities that are not fully utilized or required by businesses, use a moderately simple computerized system such as a spreadsheet application or other inventory control legacy system to monitor and control the level of their food products inventories. Such systems consider food product type, price, destination, and history, including expiry date and quantity. Another advantage provided by these systems is the ordering history and the best price paid.

Using such systems gives the business the best control of the inventory level and associated costs. However, they are unable to determine the optimal reorder level of food products, especially when food deterioration is subject to an expiration date and when products have a short life cycle before being valid for human consumption.

Therefore, due to the adoption of inappropriate inventory control strategies provided by legacy systems related to deteriorating food products, under a crucial constraint of expiration date, purchases of products that are not used to satisfy customers' demand might lead them to be surplus and, subsequently, pass their expiry date and become inappropriate for human use. This poor inventory practice is the result of legacy software not identifying the optimal reorder level of such food products, including when and how many to buy. This practice will also lead to high levels of waste of such products and drive businesses to bear high costs of both purchasing and holding.

Businesses need to be equipped with more sophisticated inventory control systems, especially for food products subject to expiry date and must adopt specialized mathematical optimization models to achieve the best inventory control of deteriorating food products. Hence, the aim of this paper is to develop an optimization model for the most effective inventory control practice of food products subject to the expiration date with a short life span. This practice considers all the incurred costs to achieve the best reorder levels of products based on predicted consumption rates.

3 LITERATURE REVIEW

Many previous studies investigated the inventory control problem of food deteriorating products affected by demand. Some of these studies include but are not limited to Taleizadeh et al. (2013), who developed an Economic Order Quantity (EOQ) model for perishable products to determine the optimal order and shortage quantities of a perishable item when the supplier offers a special sale. The same author in 2014 developed two classic models for EOQ with and without shortage subsequent payment for non-perishable products, where the objective function for the annual total costs consists of fixed cost, purchasing cost, capital cost before receiving products and holding cost including capital cost after receiving products. Tavakoli and Taleizadeh (2017) developed a classic EOQ model for decaying items with full advanced payment and conditional discount consisting of no shortage, complete back-ordering shortage, and partial lost sale is permitted to help the vendors and buyers to offer and select the best full advanced payment scheme.

The traditional non-perishable (EOQ) model could be used with perishable goods under specific holding costs and lifetime (Dobson et al., 2017). Although most inventory models, including the EOQ ones, do not consider storage capacity when stocking items. This assumption is made to satisfy any future demands and discard the perishability of products (Damgaard et al., 2012). Mishra et al. (2013) developed a deterministic inventory model with time-dependent demand and time-varying holding cost. An order-level inventory system for deteriorating items with the demand rate as a ramp type function of time was implemented. The model is solved analytically by minimizing the total inventory cost for the business enterprises (Manna et al., 2016).

Regarding time-dependent demand with inventory deterioration, Kamal et al. (2011) analyzed the developed inventory model with deterioration and partial backlogging from a different point of view to minimize the total cost associated with the inventory system. Ahmad et al. (2016) discussed four inventory control models in the food and beverage processing industry, which are the Make-To-Stock (MTS), Make-To-Order (MTO), Economic Order Quantity (EOQ), and hybrid of MTS-MTO models, to ensure that an organization can meet customer demand at the lowest possible cost to maximize profitability. Vijayashree and Uthayakumar (2015) proposed a model for the inventory planning problem with parabolic holding cost and salvage value for items that deteriorate linearly with time. Díaz et al. (2020) proposed a mathematical model to derive the EOQ under specific conditions to minimize the expected management cost of perishables, assuming constant demand and linearly decreasing purchase probability during the product life cycle. The goal is to find an optimum cycle time and order quantity. Chih-Chin (2013) proposed a model for inventory prediction and an intelligent inventory management system for the food-processing-and-distribution industry for perishable foods. In the grocery retailing industry, perishable products within the grocery-food category account for approximately 50% of supermarket sales (Freddy and Fidel, 2020). So, inventory costs and management expenses can reduce warehouse efficiency.

Azadeh et al. (2017) proposed a genetic algorithm-based approach to solve the inventory routing problem with transhipment of a single perishable product to achieve the best solution and meet customer demand under the maximum level policy. Zhang et al. (2016) developed the first approximation algorithm for periodic-review of perishable inventory systems with setup costs, where the model allows for correlated demand processes that generalize the well-known approaches to model dynamic demand forecast updates. The main idea is to decompose the total cost in terms of the marginal costs of individual decisions. The decision in period t was associated with its affiliated cost contributions to the system. These marginal costs may include costs (associated with the decision) incurred in current and subsequent periods. Kehinde et al. (2020) adopted the ABC analysis and EOQ technique to determine each inventory item's degree of importance, using EOQ for the inventory of deteriorating products items (flour, sugar and butter) to minimize total cost. Susanto (2018) used (EOQ) model to minimize the total cost of raw material inventory more economically under the production needs. This method applies two types of cost, carrying and ordering costs, making the total inventory cost more economical and reducing storage cost swelling. Nasution et al. (2020) studied the inventory planning system for the industries producing nondurable goods to reduce the number of expired products and find the optimal order quantity and time of ordering goods together (joint order). The optimal order quantity is planned with the EOQ method.

In Saraswati et al. (2017), a genetic algorithm based on total inventory cost minimization was used to determine the batch size of raw materials' multi-product. Nonetheless, inventory holding costs were based on the warehouse space and the unit's space dimension. Rabbania et al. (2018) study is devoted to the EOQ-model building, considering assumptions like deteriorating inventory quality, shortages, inventory space availability, and the overall budget for purchasing goods. Two metaheuristic algorithms, Simulated Annealing and Tabu Search, are used to minimize the total inventory cost, including ordering and holding costs of the supply chain. Obeidat et al. (2020) proposed an approach for managers and marketers to maximize profits by increasing sales of food products through genetic algorithm (GA) optimization. Sandeep and Sarvesh (2020) formulated an inventory policy for perishable products where shortages are fully backlogged, and the allowed delay in payment is influenced by order of quantity. This study aims to maximize the total profit by finding the optimal ordering quantity and length of cycle order of the retailer. Mishra (2021) provided an up-to-date review of the role of GA in overall inventory and supply chain management. Mathematical and logical analysis of different inventory and supply chain models helps managers reduce overall costs and generate higher revenue.

Many other studies show the importance of GA in identifying the optimal solution in inventory models, such as (Shakeel et al., 2012), who used GA to optimize ordering quantity at the best reorder point. In addition to the problem of inventory deterioration accompanying perishable goods, researchers interested in addressing limited storage (Junfeng et al., 2013) studied the inventory model of the deterioration units to a slope demand type with flexibility in working conditions. This paper compared the total inventory cost of two policies (EOQ-based continuous review policy and periodic review policy) in applying blood plasma inventory to select the most appropriate policy given budget constraints. The total inventory annual cost is the summation of annual setup cost, annual holding cost, annual safety stock holding cost, and annual monitoring cost. Singh and Soni (2020) developed an EOQ inventory model using ramp-type demand with deterioration and shortages in which inventory is depleted not only by demand but also by deterioration. The objective is to find the optimal order quantity to keep the total relevant cost minimum, depending on three types of cost: holding, shortage, and deterioration. Cenk (2020) extends the standard EOQ inventory management model to the case where inventory holding costs compound and show that the standard model underestimates the total annual costs. Abigail and Hanni (2021) used five steps to get the optimal result of the EOQ model to minimize the total inventory cost for a perishable powdered drink company. Sandesh and Raosaheb (2020) proposed a GA to solve deterioration inventory models to determine the optimum pro[FB01?]t and economic order quantity under various assumptions, such as the demand per unit time. Patriarca et al. (2020) presented an EOQ inventory control model for perishable items with a demand rate variable over time and dependent on the inventory rate. The model also considers the potential for backlogging and lost sales. This paper intends to provide an analytical formulation to deal with uncertainty and time-dependent inventory functions for various perishable products. The formulation is designed to support decision-making for identifying the optimal order quantity, considering costs related to perishable products, the uncertainty of demand and quality level, and the associated effect on customers, i.e. back-ordering or lost sales. Samithamby (2019) illustrated the basic EOQ model from a learner's point of view to minimize the Total Incremental Cost (TIC) beyond the cost of purchasing a product/material in consideration of two main total costs: Total Ordering Cost (TOC) and Total Handling Cost (THC). The formulation is designed to support decision-making for identifying the optimal order quantity. Edalatpour and Mirzapour (2019) developed a method to find the optimal value of perishable complementary and alternative items pricing for a multi-product EOQ model to reduce the total cost. At the same time, Thinakarana et al. (2019) provided an excellent survey to review and discuss the EOQ & EPQ models with essential parameters.

Each of the works above presented different total purchasing cost formulations from a different viewpoint related to the methodology for optimizing total cost, EOQ and/or reorder level.

This study introduces a new Total Annual Inventory Cost (TAIC) formulation for the classical purchasing with a no shortage inventory model for the best inventory control practice. This formulation is unique and specifically proposed to suit the new GA model developed in this study with a unique chromosome structure that accommodates different reorder level patterns of deteriorating food products to achieve minimal inventory costs.

4 METHODOLOGY

4.1 Inventory Control

An effective inventory control policy allows the company or organization to determine the optimal quantity of stock at the right time and place, to meet orders and avoid shortages or use them later (Misra and Sebastian, 2013; Abed and Al Salami, 2021). This applies to raw materials entering any production and finished product (Yadav et al., 2017). This policy is intended to accurately reduce inventory costs and management to prevent fluctuations in the fixed demand rate after stock withdrawals (Dania, 2010; Adediran et al., 2019). As a result, the researchers have a different set of costs as follows (Al-Jawad, 2013, p.151):

1. Item cost (C): the unit cost of purchasing the product as a part of an order.
2. Ordering (Set up) cost (C_O): These costs are independent of the order size. It is incurred when purchasing goods from a supplier, such as (labor, transportation, order checking, and telephone); also, it is incurred when producing goods for sale to others, such as (cleaning machines, calibrating equipment, and training staff).
3. Holding (Carrying or Storage) cost (C_h): These are the various costs related to warehouse inventory. It usually includes the bank interest rate on loans, returns, insurance costs, taxes, depreciation, obsolescence, damage, etc. These costs are calculated based on the retention

costs per unit stored in one year. The standard carrying cost value is usually 25% of the inventory value (James and Douglas, 1987).

4. Shortage (Unsatisfied Demand) cost (CS): These costs result from increased demand for the quantity stored in the warehouse. These costs include the cost of loss (sales opportunities, customers) and the fines paid by the company in breach of contracts with them.

4.2 Deterministic Models

This model assumes the deterministic constant value of each year-round demand, purchase cost per unit, and delivery time (Bor-Ren, 2004; Al-Jawad, 2013, p.152). The parameters of this model are introduced as follows:

Q: The number of items to order.

D: Annual demand, which is fixed (unit/time).

C: Purchase cost of each item.

C_h: Annual holding cost for each unit.

C_O: Fixed cost of placing an order. It is independent of the order size or the number of items and orders placed.

The purchasing with no shortages model assumes that the ordered items arrive instantaneously, and we do not allow any shortage. Also, the quantity we order is always going to be the same. This situation is illustrated in Figure 1 (Nahmias, 1982; Junfeng et al., 2013; Al-Jawad, 2013, p.152).

For this model, we have (Abigail and Hanni, 2021):

$$The\ Economic\ Order\ Quantity\,(Q) = \sqrt{\frac{2DC_O}{C_h}} \tag{1}$$

$$The\ number\ of\ orders\ item(N) = \frac{D}{Q} \tag{2}$$

$$The\ time\ between\ orders(T) = \frac{1}{N} = \frac{Q}{D} \tag{3}$$

$$\begin{array}{c} The\ Total\ Cost \\ per\ year\,(K) \end{array} = \overbrace{\frac{D}{Q} \times C_o}^{Annual\ Ordering\ Cost} + \overbrace{\frac{Q}{2} \times C_h}^{Annual\ Holding\ Cost} = \sqrt{2C_ODC_h} \tag{4}$$

The EOQ model can be developed by considering the purchase costs (C). Eq. (4) can be reformulated to obtain the total costs (TC) as follows:

$$Total\ Cost = Purchase\ cost \times Demand\ of\ raw\ material + The\ Total\ Cost\ per\ year(K) = C.D + K \tag{5}$$

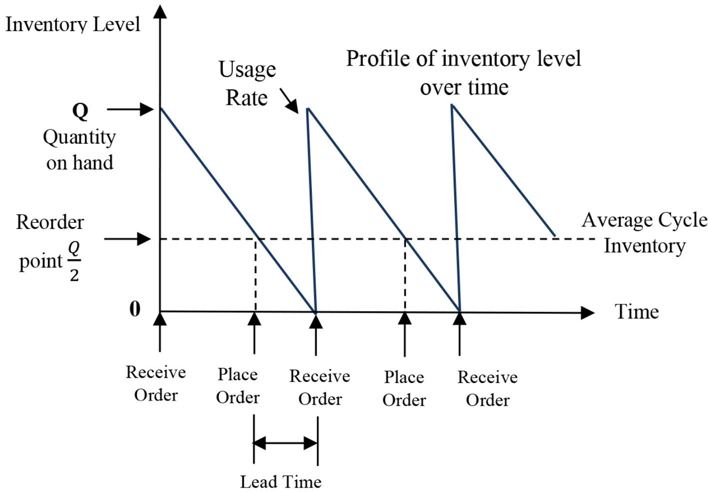

Figure 1 – Inventory level as a function of time.

Source: Created by researchers based on Junfeng et al. (2013); James and Douglas (1987, p.152).

4.3 Genetic Algorithms

A GA can be used to identify the optimal solution for optimization and research problems by reducing the total inventory cost, including the cost of purchasing products and holding inventory. The crossover and mutation operators are applied to the initial data to obtain a new generation of chromosomes (Misra and Sebastian, 2013). One of the essential aspects of controlling GA performance is choosing the appropriate method. There are many ways to represent chromosomes (Somnath et al., 2006):

1. Binary Encoding.
2. Rational Encoding.
3. Integer Value Encoding.
4. Character Representation Encoding.
5. Tree Representation Encoding.

Here, the encoding refers to mapping the problem parameters to a chromosome; we used binary encoding to represent chromosomes.

4.3.1 Fitness Function (FF)

In EOQ model-based GA, FF can be used to test the quality of chromosomes within its population. This is part of GA, defined as a criterion of the goodness of a chromosome. It ensures that the evolution is optimized (Somnath et al., 2006, Gunwoo et al., 2012). By using FF in Eq. (6) we can minimize the total inventory cost (TC) for all months depending on Eq. (5) as follows:

$$\underbrace{\begin{array}{c}\textit{Cost for}\\ \textit{Month}\left(M_j\right)\end{array}}_{\forall j=1,2,\ldots,12} = TC = \sum_{\forall i=1,2,\ldots,n}\left[\begin{array}{c}\textit{Demand of raw}\\ \textit{material}\,(i)\end{array}\times\left[\begin{array}{c}\textit{Purchasing}\\ \textit{Cost}(i)\end{array}+\left\{\begin{array}{ll}\begin{array}{c}\textit{Holding}\\ \textit{Cost}\,(i)\end{array} & \textit{if binary No.} = 0\\ \begin{array}{c}\textit{Ordering}\\ \textit{Cost}\,(i)\end{array} & \textit{if binary No.} = 1\end{array}\right\}\right]\right]$$

$$TC = \sum_{\forall i}\left[D(i)\times\left[C(i)+\left\{\begin{array}{l}C_h\,(i)\,\textit{if binary No.} = 0\\ C_o\,(i)\,\textit{if binary No.} = 1\end{array}\right\}\right]\right] \tag{6}$$

4.3.2 The proposed GA models

Figure 2 shows the steps of GA's developed model used in this paper as follows:

1. Input the inventory model's data in a matrix format for (Demand, Purchasing Cost, Holding Cost, and Ordering Cost).
2. Run GA to start generating a random binary matrix [12 months × 15 different genes] as initial population generation.
3. Calculate FF for all months per year by converting the binary matrix [12×15] to the cost matrix [12×15], arranging it in ascending order and finding TAIC.
4. The algorithm's operations begin as:

   A. Determine how chromosomes are arranged and selected.

   B. Generate a new generation by applying the principle of crossover & mutation.
5. Create a new binary matrix [12×29] for the research population. This includes the integration of an initial random binary matrix [12×15] in step 2 with the newly generated matrix [12×14] after crossover & mutation processes in step 4.
6. Calculate FF again for all months per year for step 5 above.
7. Construct the optimal costs matrix [12×29] for FF in step 6.
8. Verify the solution: has the optimal value for FF been reached? If yes, let the optimal value equal the final value.
9. Check the algorithm's termination rule:

   A. If yes, the algorithm's output is obtained (No. of Generation, Optimal Annual Min. Total Cost, Optimal Gene), and the algorithm is finished.

   B. Alternatively, arrange the optimal cost matrix in step 7 in ascending order, take the first 15 rows from the corresponding binary matrix [12×29] created in step 5 as an initial population generation and go to step 3.

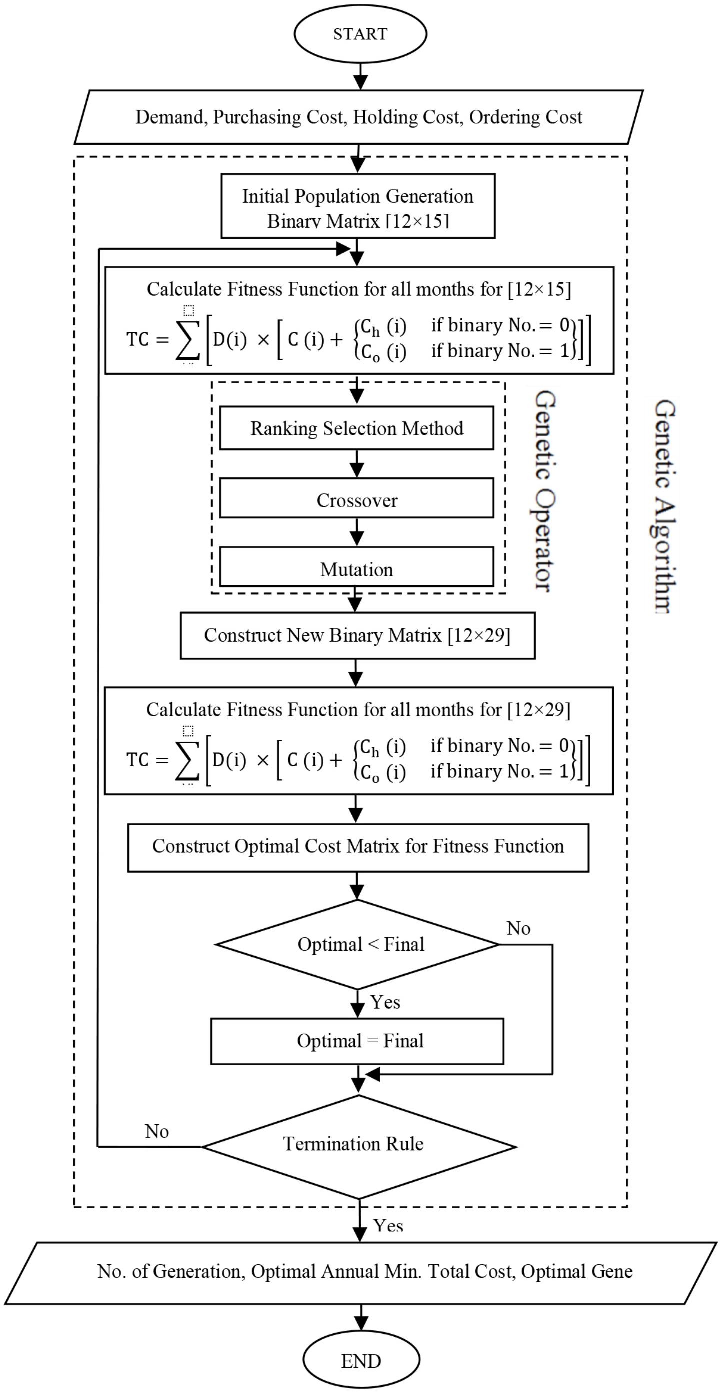

Figure 2 – The Genetic Algorithm Flowchart.

Source: Created by researchers

4.3.3 Crossover and Mutation Operators

In order to create new chromosomes, recombining strings (component materials) is conducted using simple analogies of genetic crossover and mutation operator. Crossover is the primary instrument of variation and innovation in GA to obtain better characteristics and form the most suitable solution among generations (Mahjoob et al., 2021). Mutation includes flipping the bit at a randomly chosen locus (i.e. a symbol replaced at a randomly chosen locus with a randomly chosen new symbol), and its operator is a local optimization method. Another point to be taken into account is that GA gathers the utilization of previous results to explore new areas of the search fields. Different ways of crossing-over genes within chromosomes were previously used. Examples are one-point, two-points, multiple-points and uniform crossover (Somnath et al., 2006, Gendreau and Potvin, 2010, p.112, Shakeel et al., 2012).

A one-point crossover operator is selected (Ramadas and Nandihalli, 2018). We did this operation by using two rankings. First, we choose a crossover point after 4 bits; secondly, we choose a crossover point after 2 bits. Then split parents at this point, finally creating off-springs by exchanging tails (a new 7 rows), as explained in Table 1.

Table 1 – Examples of ranking before and after crossover operation.

Original Chromosome	First Ranking (1st R)					Second Ranking (2nd R)			
	Before crossover		After crossover			Before crossover		After crossover	
00110111	**0011**	0111	0111	**0011**		00	**110111**	**110111**	00
10110011	**1011**	0011	0011	**1011**		10	**110011**	**110011**	10

The 2nd operation of GA techniques is mutation. In the (1st R), the 2nd & 7th-bit positions are interchanged, while the 1st & 8th-bit positions are interchanged.

In the (2nd R), the positions of the 3rd & 6th bit are interchanged, and the positions of the 4th & 5th bit are interchanged, which is done to ensure we will generate a new gene (this means a new 7 rows), as explained in Table 2.

Table 2 – Examples of ranking before and after mutation operation.

Original Chromosome	First Ranking (1st R)			Second Ranking (2nd R)	
	Before mutation	After mutation		Before mutation	After mutation
00011011	0 **0** 0 1 1 0 **1** 1	0 **1** 0 1 1 0 **0** 1		0 0 **0** 1 1 **0** 1 1	0 0 **0** 1 1 **0** 1 1
10010100	**1** 0 0 1 0 1 0 **0**	**0** 0 0 1 0 1 0 **1**		1 0 0 **1 0** 1 0 0	1 0 0 **0 1** 1 0 0

4.3.4 GA Termination Rule

The evolution process starts when GA moves from one generation to another, improving the quality of chromosomes until the termination condition is reached. The best-utilized halting is when the quantity of cycles has achieved the greatest generation. Here we halted when the end criteria were fulfilled, which is done when the contrast between the complete yearly stock expense for the principal 15^{th} least columns of (generation #n) and a similar expense of (generation #n+1) ends up zero, the GA procedure stop when we got the esteem (zero) 3 times in a row, indicating that no improvements would follow.

5 CASE STUDY, RESULTS DISCUSSION AND SENSITIVITY ANALYSIS

5.1 Case Study

Erbil Rotana Hotel, located in the northern part of IRAQ, is considered as a case study to verify the developed inventory based on GA. This hotel was established in 1992. In this paper, we tried to solve a problem of inventory faced by Rotana Hotel to identify the optimal inventory level for reducing costs.

The first beach was opened in 1993 in Rotana Abu Dhabi. This hotel has now the best leading hotel management companies in the Middle East, Africa, South Asia and Eastern Europe (Rotana Hotel Management Corporation, 2020). In Rotana Hotel restaurants, many raw materials come into the working process. All the raw materials (387 different items) are used and listed in n=8 groups depending on their type, as given in Table 3.

In Table 3, holding costs vary between 0.04105 – 0.05495 per month (about 0.4926 – 0.6594 per year), which is the acceptable range for Rotana Hotel, while the ordering cost acceptable range is between 0.03098 – 0.04501 per month. The average weighted price (AWP) (Eq. (7)) (ID (Iraqi Dinar) /Kg) is calculated using the general formula Eq. (1) (Almir and Dejan, 2013).

Researchers reformulated Eq. (7) represents the Purchasing Cost (C(i)) in Eq. (6).[1]

$$AWP\ for\ Group_i = \frac{\sum_{\forall j}\sum_{\forall k} Q_{jk}.P_{jk}}{\sum_{\forall j}\sum_{\forall k} Q_{jk}}, \forall i = 1,2,\ldots,n \tag{7}$$

Where j: no. of the type contains in group i for all j.

k: no. of items in type j in group i for all k.

Q_{jk} : the quantity of item k in type j (Kg/item) for all j & k.

P_{jk} : the price of item k in type j (ID/item) for all j & k.

Using Eq. (7), we have the AWP for each group as follows:

$$\underbrace{AWP\ for\ G_1}_{\forall j=1,2,3,4,5} = \frac{\overbrace{[\sum_{k=1}^{5} Q_{1k}P_{1k}]}^{Butter} + \overbrace{[\sum_{k=1}^{18} Q_{2k}P_{2k}]}^{Cheese} + \ldots + \overbrace{[\sum_{k=1}^{3} Q_{5k}P_{5k}]}^{Milk}}{\sum_{k=1}^{5} Q_{1k} + \sum_{k=1}^{18} Q_{2k} + \ldots + \sum_{k=1}^{3} Q_{5k}} = 5442\ ID/Kg$$

[1] Hint: In Table 3, to change any liquid materials quantity from Littre to Kg, we depending on (1 Littre water = 1 Kg) in water temperature which is 3.98 C^0 and atmospheric pressure record, so, the same things did with any liquid materials density.

$$\underbrace{AWP\ for\ G_2}_{\forall j=1,2,\ldots,6} = \frac{\overbrace{[\sum_{k=1}^{9} Q_{1k}P_{1k}]}^{Tomato\ Pastes} + \overbrace{[\sum_{k=1}^{20} Q_{2k}P_{2k}]}^{Sauces} + \ldots + \overbrace{[\sum_{k=1}^{7} Q_{5k}P_{5k}]}^{Sea\ Food}}{\sum_{k=1}^{9} Q_{1k} + \sum_{k=1}^{20} Q_{2k} + \ldots + \sum_{k=1}^{7} Q_{5k}} = 6895\ ID/Kg,\ and\ so\ on.$$

Most experts in industrial companies seek to reduce the total holding costs of maintaining inventory, which range from 18% per year to 75% or between 25-55% (Richardson, 1995). The quantity of raw materials used per month (during 2019, depending on the inventory records for Rotana Hotel) is presented in Figure 3.

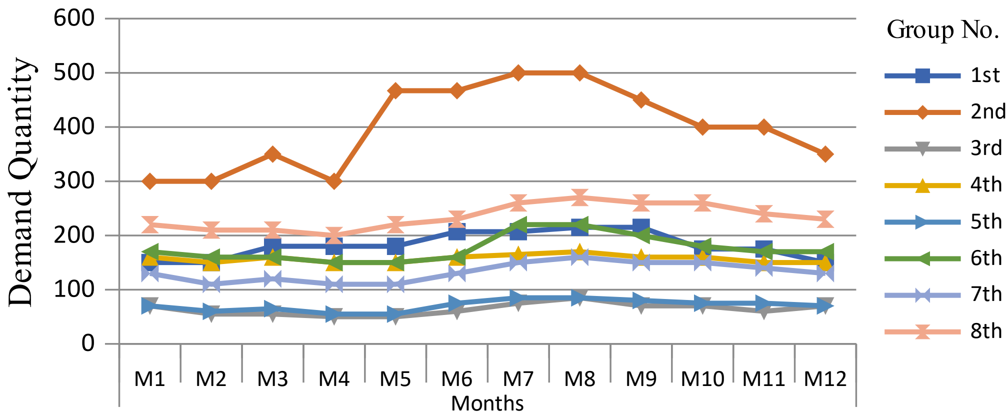

Figure 3 – Demand for raw material for each group (Kg/Month).

In Figure 3, high annual demand for raw materials is observed in March because it has a national holiday day that most people celebrate by seeking hotels and other public leisure facilities. Most hotels located in the north of Iraq get busy during summer time (May-Aug) because large numbers of tourists from middle and southern parts of Iraq seek this part of the country to enjoy the weather. Then, facilities and, hence, demand on food raw materials increase dramatically. These attributes of this part of Iraq being relatively stable, and the security situation under control, attract more customers to seek this part of the country of leisure. Political stability's impact on the tourism sector's development has already been investigated (Bayar and Yener, 2019).

5.2 Chromosome Representation

In the Rotana Hotel case, there are n=8 groups of raw materials representing the 12 months. Every month is generated randomly as 15 different genes (this represents forecasting for the next 15 years, and there is no need to maximize this period). Each gene length consists of 8 numerical values, and anyone represents one group to make a chromosome using a C++ program developed by the researcher. This program generates 12 months × 15 different genes = 180 genes. This group of chromosomes is an initial population. Now, these 8 values are to be encoded to binary

Table 3 – The various types and costs of raw materials.

Group No.	Type	Type's contain	No. of items in each type	Total of items in each group	Average weighted Price (ID/Kg)	Holding Cost (ID/Kg)	Ordering Cost (ID/Kg)
1st	Dairy products	Butter Cheese Yoghurt Ice cream Milk	5 18 4 6 3	36	5442	272	174
2nd	Canned goods of all kinds	Tomato pastes Sauces Jams Fresh beans Dried fruit Seafood	9 20 26 15 11 7	88	6895	310	290
3rd	Appetizers	Chips French fries Olive	9 8	17	5893	324	259
4th	Biscuit & Chocolate	Biscuit Corn Flakes Chocolate	3 7 52	62	6377	332	287
5th	Spices & Condiments	Spices Condiments	46 25	71	9500	390	389
6th	Dry food	Vegetable oils Pasta Rice, Sugar & Flour	8 17 15	40	2905	143	90
7th	Meat	Beef Lamb Chicken Fish	4 4 9 11	28	13816	746	580
8th	Drinks	Tea Coffee Soft drinks Juice Water	12 11 7 6 9	45	4524	217	190

(0,1) as shown in Table 4, where 0 will represent holding cost and 1 will represent ordering cost, as shown in Table 5. We can generate random numbers by Microsoft Excel as another method, a computer system with built-in rand ( ) functions, as explained in Gendreau and Potvin (2010, p.132).

Table 4 – Gene representation for each month.

Month	$M_j \ \forall j = 1,2,\ldots,12$							
Group No.	1	2	3	4	5	6	7	8
Gene	↑	↑	↑	↑	↑	↑	↑	↑

Binary code (0 or 1)

Table 5 – The Generated Chromosomes.

	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12
1	00110011	01100110	00111000	11011011	01101010	00011011	01110000	00001100	00000111	01100101	11010100	01111100
2	00111010	11011000	01110110	01101100	00110101	01100110	10101011	00101100	00001100	01100000	11010001	01110111
3	01010111	10001101	11101110	10000011	10111010	10010101	11101010	10111101	11111000	00111000	10010011	11100010
4	01110110	10110011	10111010	01001100	00001100	01111110	00100111	01110000	11101100	11111000	00011100	10001100
5	10010000	00011111	00101100	11010100	00110110	00001100	00001100	10101011	11000111	10110111	00100001	10010010
6	10000111	01111101	10110111	01010000	01011000	00011110	00101100	11101010	01011111	10000101	00110010	00001101
7	01111101	00110111	01111010	01110000	01010111	01110001	10111101	00100111	01110110	01101101	10100000	11111000
8	00110111	11100011	10010101	10101011	11011101	01011111	11101110	00001100	10110000	00011110	10001100	11101100
9	11100011	10110101	01111110	11101010	10101100	01110110	01100010	11111000	10001101	01110001	00111000	11000110
10	10010100	00011011	00001100	00100111	10100011	10110000	00011000	11101100	10000000	01011111	01010101	00011011
11	10110011	01100110	00011110	00001100	10001101	10001101	01101111	11000111	10000111	01110110	01110101	00100101
12	10010110	01010111	01110001	00101100	00110110	00110110	10110011	00011001	01011110	10110000	10010011	10010011
13	00010000	01110110	11001010	01100100	10110101	11011001	10101001	00100101	01010100	00001101	00000110	00000110
14	10110101	10010000	11011001	00101101	11100011	11010100	10100001	01011110	00111001	10110111	11111100	11111100
15	00011011	10000111	10011000	00100010	10110101	01010000	00100111	10000011	01100010	01011000	00000111	00000111

5.3 Fitness Function for Current Model

Depending on the C++ program and GA flowchart in Figure 2, firstly, we can generate the binary values (the chromosome of GA) as in Table 5; secondly, depending on FF in Eq. (6), we convert this Table to cost Table for all months as shown in Table 6.

From Table 5, the binary string for M_1 in Row_1 is (00110011), so we can apply it in Eq. (6) as follows to get the total inventory cost for all groups in M_1 associated with the above string. After that, we can put it in Table 6:

$$\begin{matrix} \therefore Cost\,for \\ Month\,(M_1) = \\ \in Row_1 \end{matrix} \begin{matrix} 150\,(5442+272)+300\,(6895+310)+70\,(5893+259)+160\,(6377+287)+ \\ 70\,(9500+390)+170\,(2905+143)+130\,(13816+580)+220(4524+190) \end{matrix} = 8634500$$

We continue in the same way until the binary string for M_{12} in Row_{15} which is (00000111), so:

$$\begin{matrix} \therefore Cost\,for \\ Month\,(M_{12}) = \\ \in Row_{15} \end{matrix} \begin{matrix} 150\,(5442+272)+350\,(6895+310)+70\,(5893+324)+150\,(6377+332)+ \\ 70\,(9500+390)+170\,(2905+90)+130\,(13816+580)+230(4524+190) \end{matrix} = 8977540$$

Now, we will arrange the total costs column in Table 6 in ascending order for all genes of population generation to determine the minimum cost string as shown in Table 7. At this point, we will leave the first row as it is (row no. 3) because it has a minimum cost among 15 rows, while we apply the crossover procedure for the next 7 old rows (11, 8, 14, 9, 12, 7 and 6), and apply the mutation for the last 7 old rows (5, 15, 4, 2, 1, 10 and 13) to get a new generation of genes.

5.4 Initial Population Generation

As explained before, a crossover operator did this by using two rankings. Depending on Table 7, we perform these two rankings by selecting chromosomes from the 7 old rows. After the crossover operation, two new chromosomes are generated (meaning a new 7 rows).

Table 6 – The inventory cost for all groups of every gene.

	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	Total
1	8634500	8009080	8828385	8004285	9325540	10171848	11264428	11609440	10754630	10068820	9656840	8986960	115314756
2	8640370	8017885	8793050	8041135	9332555	10163613	11229562	11603915	10786470	10085380	9659370	8959240	115312545
3	8624040	8016485	8782545	8017090	9310490	10164737	11226582	11567905	10755250	10086105	9644130	8966510	115161869
4	8625430	7996440	8790825	8044385	9348440	10156338	11238273	11598010	10751850	10060955	9681915	8990560	115283421
5	8651870	8006175	8827105	8020050	9320235	10198358	11274983	11560655	10724560	10027570	9687370	8971310	115270241
6	8622540	8014860	8776740	8045640	9340300	10169578	11270108	11557945	10738350	10064220	9663860	8999050	115263191
7	8641000	8002660	8801465	8042390	9308205	10180263	11235377	11570150	10740900	10068745	9676700	8981270	115249125
8	8625490	7997190	8800235	8013785	9308770	10154028	11214922	11609440	10764330	10056215	9671515	8979010	115194930
9	8621000	8006220	8792985	8013185	9327550	10156413	11246953	11576855	10758380	10071160	9687025	8962050	115219776
10	8642860	8014655	8830680	8023530	9311355	10175527	11279218	11572845	10776080	10041195	9667510	8979730	115315185
11	8619800	8009080	8803560	8050385	9324860	10171862	11228188	11544605	10733560	10043740	9663610	8994570	115187820
12	8621280	8000235	8815780	8047135	9320235	10165753	11222222	11606160	10745370	10069030	9644130	8965100	115222430
13	8666570	8002330	8794600	8041190	9314915	10163802	11254462	11596710	10770350	10081295	9665500	8983750	115335474
14	8632370	8023945	8801650	8041735	9302015	10161607	11254547	11565230	10778300	10027570	9652865	8972260	115214094
15	8638980	7998285	8814320	8036880	9314915	10190373	11238273	11566265	10758700	10082655	9659020	8977540	115276206

Table 7 – The total cost of 15 strings in ascending order.

<table>
<tr><th>New row no.</th><th colspan="2">Old row no.</th><th>Total</th><th>New row no.</th><th colspan="2">Old row no.</th><th>Total</th></tr>
<tr><td>1</td><td colspan="2">3</td><td>115161869</td><td>9</td><td rowspan="7">Mutation Process</td><td>5</td><td>115270241</td></tr>
<tr><td>2</td><td rowspan="7">Crossover Process</td><td>11</td><td>115187820</td><td>10</td><td>15</td><td>115276206</td></tr>
<tr><td>3</td><td>8</td><td>115194930</td><td>11</td><td>4</td><td>115283421</td></tr>
<tr><td>4</td><td>14</td><td>115214094</td><td>12</td><td>2</td><td>115312545</td></tr>
<tr><td>5</td><td>9</td><td>115219776</td><td>13</td><td>1</td><td>115314756</td></tr>
<tr><td>6</td><td>12</td><td>115222430</td><td>14</td><td>10</td><td>115315185</td></tr>
<tr><td>7</td><td>7</td><td>115249125</td><td>15</td><td>13</td><td>115335474</td></tr>
<tr><td>8</td><td>6</td><td>115263191</td><td colspan="3">Total cost for 15 rows</td><td>1728821063</td></tr>
</table>

While the 2^{nd} operation (mutation) for the population chromosome is selected from the last 7 old rows, in the (1^{st} R), the positions of the 2^{nd} & 7^{th} bit (in rows 5, 15 and 4) are interchanged, and the positions of 1^{st} & 8^{th} bit (in rows 2, 1, 10 and 13) are interchanged. In the (2^{nd} R), the positions of the 3^{rd} & 6^{th} bit are interchanged, and the positions of the 4^{th} & 5^{th} bit are interchanged. So, we have now 29 strings after crossover & mutation [row no. 3 + (14 rows before + 14 rows after) crossover & mutation]. This represents forecasting for the next 29 years, and the population size after the GA process becomes 12 months × 29 different genes = 348 genes. Depending on Eq. (6) and C++ program, Table 8 will be constructed after arranging the cost in ascending order.

The best fitness result for the initial population size of 180 genes and the optimal inventory cost/month are shown in Figures 4 and 5, respectively, depending on the two ranking types (1st R & 2nd R). Table 8 shows that rows 21, 19 and 18 (generated by crossover & mutation operations) have the minimum cost. Finally, we select the first 15th minimum rows from Table 8 as a second initial population to start the 2nd GA process. The TAIC for this 15th row is equal to (1728054215) ID. The difference between it and the initial cost (1728821063) ID from Table 7 equals (766848) ID. All previous GA processes did one time using the C++ program to show the GA process step by step until we get the optimal inventory cost, as explained later in Table 9.

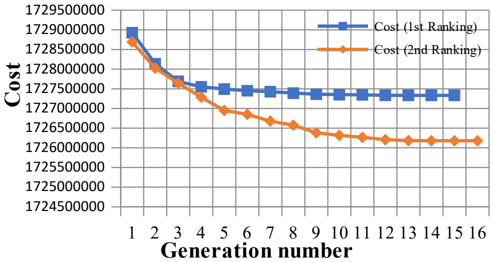

Figure 4 – Best fitness result for pop. size 180 genes.

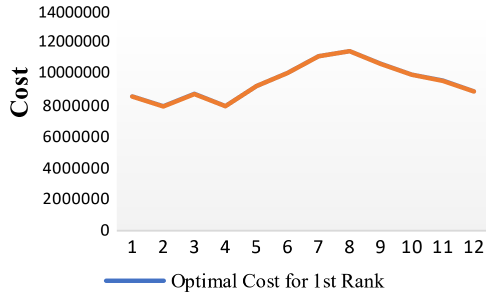

Figure 5 – Optimal inventory for pop. size 180 genes.

Table 8 – The ascending order for a total cost of 29 strings.

Rows No.	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12	Total
21	8609340	8005140	8783940	8026780	9323215	10163443	11217012	11571450	10741080	10031140	9674435	8962770	115109745
19	8631360	8008655	8776940	8011235	9311150	10157403	11245293	11554520	10759800	10049270	9650880	8993710	115150216
1	8624040	8016485	8782545	8017090	9310490	10164737	11226582	11567905	10755250	10086105	9644130	8966510	115161869
18	8632980	8039665	8800170	8009740	9320180	10182808	11254318	11565640	10736960	10046185	9633795	8955770	115178211
2	8619800	8009080	8803560	8050385	9324860	10171862	11228188	11544605	10733560	10043740	9663610	8994570	115187820
17	8628500	8008270	8819290	8012435	9308770	10151497	11214922	11590115	10765150	10061210	9672525	8961980	115194664
3	8625490	7997190	8800235	8013785	9308770	10154028	11214922	11609440	10764330	10056215	9671515	8979010	115194930
16	8634430	8009080	8805340	8034750	9322660	10170012	11207582	11586265	10776320	10043920	9644270	8979010	115213639
4	8632370	8023945	8801650	8041735	9302015	10161607	11254547	11565230	10778300	10027570	9652865	8972260	115214094
5	8621000	8006220	8792985	8013185	9327550	10156413	11246953	11576855	10758380	10071160	9687025	8962050	115219776
6	8621280	8000235	8815780	8047135	9320235	10165753	11222222	11606160	10745370	10069030	9644130	8965100	115222430
22	8655950	7985535	8795795	8045040	9324915	10167177	11231542	11556285	10737710	10082655	9664130	8985890	115232624
7	8641000	8002660	8801465	8042390	9308205	10180263	11235377	11570150	10740900	10068745	9676700	8981270	115249125
25	8625430	8008700	8803745	8032125	9348440	10156338	11253173	11581450	10735950	10044055	9681915	8990560	115261881
8	8622540	8014860	8776740	8045640	9340300	10169578	11270108	11557945	10738350	10064220	9663860	8999050	115263191
9	8651870	8006175	8827105	8020050	9320235	10198358	11274983	11560655	10724560	10027570	9687370	8971310	115270241
10	8638980	7998285	8814320	8036880	9314915	10190373	11238273	11566265	10758700	10082655	9659020	8977540	115276206
27	8625740	8009080	8828385	8004285	9325540	10157772	11264428	11609440	10740580	10058690	9667510	8986960	115278410
11	8625430	7996440	8790825	8044385	9348440	10156338	11238273	11598010	10751850	10060955	9681915	8990560	115283421
26	8655950	8005625	8793050	8028875	9332555	10163613	11244462	11603915	10786470	10068480	9644130	8959240	115286365
20	8657210	8014920	8797955	8016490	9319655	10165883	11242423	11585175	10744910	10065935	9680545	8996760	115287861
12	8640370	8017885	8793050	8041135	9332555	10163613	11229562	11603915	10786470	10085380	9659370	8959240	115312545
13	8634500	8009080	8828385	8004285	9325540	10171848	11264428	11609440	10754630	10068820	9656840	8986960	115314756
14	8642860	8014655	8830680	8023530	9311355	10175527	11279218	11572845	10776080	10041195	9667510	8979730	115315185
28	8651620	8005625	8830680	8011290	9311355	10189603	11279218	11586625	10790130	10031065	9656840	8971240	115315291
29	8666570	8002330	8806570	8041190	9314915	10163802	11254462	11582930	10770350	10071165	9665500	8983750	115323534
23	8651870	8018435	8827105	8007790	9329155	10198358	11274983	11577215	10724560	10044470	9687370	8985890	115327201
15	8666570	8002330	8794600	8041190	9314915	10163802	11254462	11596710	10770350	10081295	9665500	8983750	115335474
24	8654560	8010545	8814320	8049140	9314915	10178133	11253173	11582825	10758700	10082655	9674260	8992120	115365346

5.5 Sensitivity Analysis

As mentioned earlier, the initial population size is 180 genes; in order to show the effect of population size on the GA outcome behavior and the optimal value of TAIC, the GA process is run twice with two different initial population sizes 12×6 = 72 genes and 12×25=300 genes.

The best fitness result for the two population sizes is shown in Figures 6 and 7, respectively, depending on the two ranking types (1st R & 2nd R). Based on Figures 4, 5, and 7, the researchers noticed that the chromosomal arrangement changes in the crossover and mutation at the (2nd R) process resulted in favorable outcomes as the lowest cost of the total inventory acquired by a significant difference comparing with the (1st R). However, the GA process required a couple more occasions of frequency number to arrive at the optimal solution and expected the small initial population size (72 genes) compared with (180, 300).

The change in the chromosomal type of arrangement did not affect the final results at the point when the population size of 72 genes appeared in Figure 6. In the two cases, the arrangement finished after 10 times of frequency number with a bit of oscillation up and down to the cost value. This volatility was not seen in Figure 4 despite the vast disparity between (1^{st} R) and (2^{nd} R), which came for (1st R), which ended with a recurrence of less than one second. Figure 7 results in a note that the lowest amount of the total costs came from the use of (2^{nd} R), although it was over 22 recurrences of a difference of 5 more iterations on (1^{st} R) that ended with less than 17 iterations. As a result, we can notice that bigger initial population size gives better results for the total inventory cost.

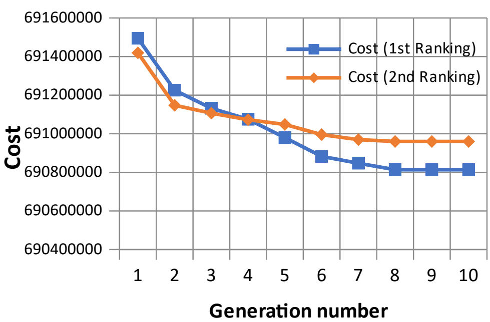

Figure 6 – Best fitness result for pop. size 72 genes.

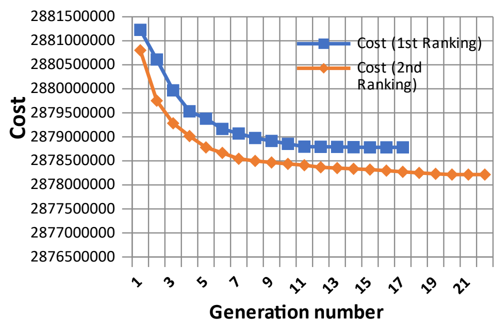

Figure 7 – Best fitness result for pop. size 300 genes.

5.6 Optimal Inventory Cost for Current Model

The outcome of the best solution can be observed in Figures 5, 8 and 9, which show the behavior of these values of various population sizes for two types of chromosomal arrangement (1^{st} R and 2^{nd} R).

It can be observed that similar behavior among these three Figures 5, 8 and 9 broadly matches the overall shape of these Figures despite some slight differences between real values compared to those values for the same month in these Figures. To conclude, only the optimal total inventory cost values can be adopted, corresponding to the order of chromosomes that gave lower total inventory cost, as represented in Figure 10.

From Figure 10, it can be seen that the best value (lowest) for the total inventory cost is obtained when the population size is 180 genes at (2^{nd} R) and of (114828814 ID), which is considered the optimal value in comparing with a population size of 72 genes of (115036099 ID). This confirms the previous concept that illustrates the inverse relationship between the population size and total inventory costs.

Table 9 shows the optimal amount (lowest) for the optimal inventory cost/month that corresponds to the best value obtained from Figure 10 when the initial size is180 at (2^{nd} R) as well as the gene corresponding to each cost.

In Table 9, we selected the minimum cost for each month to get TAIC in Rotana Hotel. To understand the impact of GA to solve the research problem, we can analyze the minimum cost for each gene in all months, as shown in Table 4, for example, in Table 10.

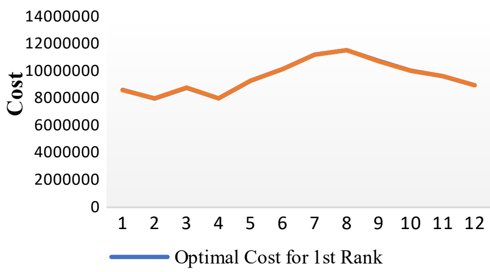

Figure 8 – Optimal inventory for pop. size 72 genes.

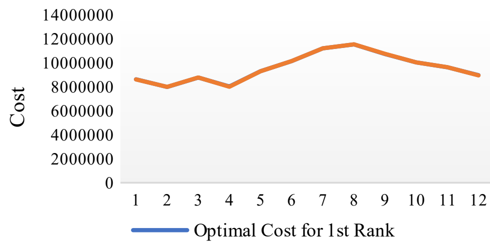

Figure 9 – Optimal inventory for pop. size 300 genes.

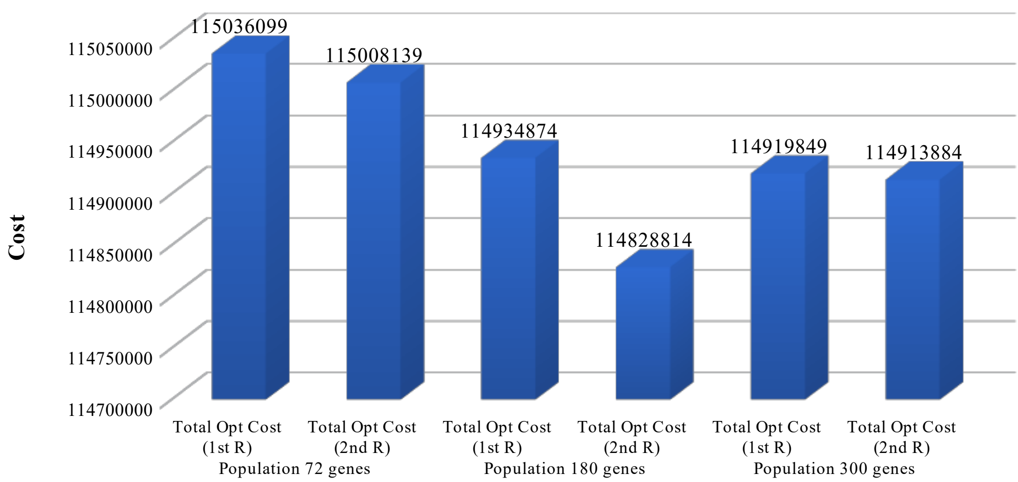

Figure 10 – Optimal Total Inventory Cost.

This means that the Rotana Hotel must make the reorder point procedure for groups numbers (1, 2, 3, 6 and 7) only in the first month (M1) to get the minimum monthly inventory cost (8617930 ID) and neglect the group (4 (Biscuit & Chocolate), 5 (Spices & Condiments) and 8 (Drinks)) without change. This process will not affect the inventory movements (input & output). In the same way, we can see these effects in the other months.

Table 9 – The Optimal inventory cost with corresponding genes.

Month	Row no.	Gene	Cost (ID)
M_1	1	11100110	8617930
M_2	26	11111111	7981900
M_3	12	11011111	8773250
M_4	0	11110110	7998540
M_5	15	11011111	9290510
M_6	18	11110111	10129917
M_7	15	11010111	11205437
M_8	26	11111111	11531345
M_9	26	11111111	10712730
M_{10}	18	11110111	10019570
M_{11}	1	11111111	9623145
M_{12}	12	11110111	8944540
Total			**114828814** ID

Table 10 – Example of analysis the minimum cost for month M_1.

Month	M_1								Cost (ID)
Group No.	1	2	3	4	5	6	7	8	
Gene	1	1	1	0	0	1	1	0	8617930

Re-order points for specific groups

Using Table 9 to indicate that the cost reduction resulting from the use of GA is access to the best value obtained when the population size of 180 genes at (2^{nd} R) and of (114828814 ID), while the highest total inventory as shown in Table 8 is (115365346 ID). The reduction percentage in possible cost can be identified in Eq. (8) as follows:

$$\textit{Cost Reduction Ration} = \frac{\textit{Normal value} - \textit{Optimal value}}{\textit{Normal value}} = \frac{115365346 - 114828814}{115365346} = 0.47 \qquad (8)$$

Note that the use of GA in inventory management in Erbil Rotana Hotel suggests the possibility of providing an abundance of stock at the cost of up to 47% of the total inventory costs. We do not know whether this is workable for the rest of the Erbil Rotana Hotel group as we do not know the applicability to the rest of other tourism sectors due to the different privacy of each sector. On the assumption that the administration official is evenly distributed throughout the Iraqi economy, it is possible to reduce the administration costs stock in each of the production units as shown in Eq. (9):

$$\frac{\textit{Cost Reduction}}{(\in \textit{Iraq})} = \frac{\textit{Inventory cost}}{(\in \textit{Iraq})} \times \frac{0.47}{100} \qquad (9)$$

However, this assumption will not be accepted for the above reasons. In this case, we recommend expanding further studies on inventory management using the GA model proposed in this research and applying it to all sectors of tourism and non-tourism to reach real transactions to reduce the costs of inventory.

5.7 CONCLUSION AND FUTURE WORK

The study contributed to the existing knowledge about inventory management of perishable food products in the tourism industry. An inventory control model for optimizing reorder points of items was developed. High-quality predictions of inventory levels have been achieved to minimize the monthly inventory cost.

A GA model was proposed for inventory level optimization. This was supported by a real-life case study of the Rotana Hotel. The reorder point procedure generated by the GA model for each group each month enabled Rotana Hotel to achieve the minimum total purchasing cost. It was also determined that the results of this research satisfied the research hypothesis that the GA has a real impact on minimizing TAIC, where larger initial population sizes represented by a larger number of chromosomes per population lead to significant improvements in the total inventory cost.

The gap between what worked in research and what works in practice, due to the lack of controlling perishable food products inventory, was also addressed. This was presented clearly by using the current moderately simple computerized system, such as a spreadsheet application or other inventory control legacy system, compared to the more complex systems proposed as a result of the research work.

Although a new model was introduced for a cost-effective inventory control solution, this model cannot handle uncertainty inherited in demand, purchasing cost, and delivery time around the year. Besides all the advantages that the developed model added to the current inventory control practice in terms of minimizing its total inventory cost, there are still a number of limitations that needs to be addressed. For instance, the proposed model has not considered the safety stock issue, as all the available materials were assumed to be able to handle the customers' orders. In addition, the deterministic aspects of this demand problem were considered in this study.

Further development of this research work includes proposing more advanced models that consider additional aspects of safety stock, unknown lead time, and quantity discount. For more accurate forecasting outputs, average values of more extended time-series data would be considered and adopted in the developed model for more accurate optimization results. Uncertainty in demand, cost and delivery time could also be modelled using other related techniques such as fuzzy logic.

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How to cite

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