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An Integrated Production-distribution Problem of Perishable Items with Dynamic Pricing Consideration in a Three-echelon Supply Chain

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ABSTRACT

The importance of employing appropriate pricing strategies for perishable products within the supply chain cannot be overstated. Pricing is a cross-functional driver of each supply chain, playing an irrefutable role in the success and profitability of the supply chain alongside other factors such as inventory and production policies which has been investigated in this research. The research emphasizes the significant role of pricing in profitability, along with the interplay of production policies and inventory control, highlighting their collective influence on financial outcomes, the subject of dynamic pricing within a multi-product, multi-period problem in a three-level supply chain with perishable products has garnered relatively limited attention. The study focuses on optimizing an integrated production-distribution system with multiple producers and distribution centers serving specific customer groups. Direct shipments between production centers, distribution centers, and retailers are optimized using a vehicle routing problem approach. A mixed-integer programming model is formulated, and a genetic algorithm-based metaheuristic approach is proposed. The BARON solver was initially used to solve two simplified test problems, with results compared to a self-designed genetic algorithm implemented in C#. After confirming the efficiency and effectiveness of our genetic algorithm (GA), the investigation is further extended to encompass five distinct problems, each comprising nine sub-problems. The GA demonstrates its power and adaptability by providing high-quality solutions efficiently within a reasonable computational time.

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1. INTRODUCTION

Effective pricing strategies play a pivotal role in the supply chain management of perishable items, including food and pharmaceuticals. Given the perishable nature of these goods, pricing decisions significantly impact various aspects of the supply chain. The right pricing approach helps optimize revenue generation while minimizing losses due to spoilage or expiration. By strategically setting prices, businesses can balance supply and demand, ensure product availability, and enhance profitability. Dynamic pricing mechanisms, tailored to factors like demand fluctuations, product freshness, market conditions, and inventory levels, enable businesses to stay competitive and maximize revenue. Moreover, pricing decisions in the supply chain of perishable items necessitate careful consideration of cost factors, market dynamics, consumer behavior, product quality, and regulatory requirements. By implementing effective pricing strategies, businesses can mitigate risks associated with perishable items, improve waste reduction efforts, optimize inventory management, and meet consumer expectations for both quality and affordability.

The delay in product delivery to customers can lead to dissatisfaction and long-term damage to a producer's credibility, resulting in reduced supply chain competitiveness. Various factors, starting from the lowest level of the supply chain with customer needs identification, influence the rapid delivery of products. It is crucial to plan and schedule operations effectively to meet these needs. Additionally, effective inventory management plays a significant role in meeting a portion of customer demands. Moreover, an abundance of

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inventory intensifies supply chain reliance and heightens the vulnerability of fashion products, such as clothes, bags, and shoes, to becoming outdated. Furthermore, industries dealing with perishable items like food, drugs, or oil and gas products face the risk of inventory reduction due to product decay when increasing inventory levels. The importance of perishable items has significantly heightened in recent years, notably due to the COVID-19 pandemic, resulting in profound alterations in the supply chain policies of retail chains and restaurants [1].

Apart from having appropriate plans for efficient production of goods, adopting appropriate policies to control inventory in a way that keeps holding cost and decay rate at an acceptable level and also meets customer needs are essential. Furthermore, if there are no efficient transportation systems providing customers with products promptly then efforts and plans aimed at production and inventory control will not be effective. Thus, integration is inevitable in every supply chain for determination of production, inventory and distribution policies to achieve strategic alignment. Achieving these goals requires the utilization of appropriate and relevant technologies associated with the industry 4.0 (I4.0). I4.0 proposes an industrialization model in which humans, machines, learning algorithms, and products communicate with each other via both physical and cybernetic means [2]. The supply chain studied in this research is a forward or traditional supply chain (SC). The forward SC, also known as the traditional SC or the linear economy of take-make- waste, is a one-directional material flow beginning with raw material extraction, continuing with the process of manufacturing a product, and ending with customers disposing of the same product after use. In the opposite direction of the forward SC, products move through the reverse SC. The reverse SC includes acquisition of the used products from customers, recovering the products' residual value, and remarketing the products [3]. The forward and reverse activities of a supply chain are combined by the Closed-Loop supply chain (CLSC) network into an integrated system with the aim of improving the economic, environmental, and social criteria; In the CLSC, a manufacturer may decide to handle the return process separately [4]. For obtaining more information about the structures of traditional and closed-loop supply chains, it is advised to refer to literature [5].

Given the importance of pricing policies used as a control lever for coordination in the supply chain [6]; this study investigates a multi-product multi-period mixed-integer programming mathematical model for a three-echelon supply chain to maximize profit. In this model, product demand is dependents on price and is determined for each period. The supply chain consists of manufacturers, distribution centers, and retailers. Manufacturers have the capability to produce all products, and a distribution center may be supplied by one or more manufacturers. Products are directly delivered from production centers to the distribution centers; while customer deliveries are managed using a vehicle routing problem. Since it is probable for customer demand for a product to exceed a vehicle's capacity, each customer may be served by multiple vehicles in this study.

The reminder of the paper is organized as follows. In section 2, the related works are reviewed in order to examine the different aspects of the research problem in terms of structure and solution methods. Then, the assumptions, notations and mathematical model are presented in section 3. Section 4 describes the framework of the genetic algorithm used to solve the problem. Computational results are provided in section 5; and finally, section 6 presents the conclusion and future research directions.

2. LITERATURE REVIEW

Modeling and solving integration problems in production, inventory, and distribution have garnered attention from researchers in recent years. This is because the integration of production and distribution not only significantly impacts the profitability of the supply chain but also enhances responsiveness to market needs. Several researchers have conducted reviews of related studies and categorized them based on different perspectives. For instance, Farahani et al. [7] have provided a comprehensive classification of integrated production-distribution models. The majority of previous studies addressing this research problem have considered the following issues:

1. Determining the quantity of regular-time and overtime production, as well as identifying the production that needs to be outsourced during each period. The inventory number of manufacturers;
2. The quantity of products delivered from manufacturer to warehouses or distribution centers;
3. The inventory of warehouses or distribution centers;
4. The quantity of backlog or lost sales on different products in each period.

Considering the complex nature of the integrated production-distribution problem and the large number of decision variables involved, researchers have often turned to heuristic or metaheuristic approaches in order to obtain efficient and effective solutions. In the following sections, we will delve into a selection of notable studies from reputable journals that have tackled this problem.

Bilgen and Günther [8], introduce a block planning approach that establishes cyclical production patterns based on setup families. The study examines two transportation modes, full truckload and less than truckload, for delivering final goods from plants to distribution centers. The proposed approach employs a mixed-integer linear optimization model to minimize overall production and transportation costs. They utilized two distribution methods, Full Truckload (FTL) and Less than Truckload (LTL), in the distribution process and finally the results of their work were evaluated through a case study conducted in a fruit juice production factory. A mixed-integer linear model was proposed by Cóccola et al.[9] to integrate production and distribution policies into a supply chain with a number of manufacturers in multi_site network. The model addresses the problem of managing single-stage parallel-line multiproduct batch plants together with multi-echelon distribution networks transporting multiple products from factories to customers through direct shipping and/or via intermediate depots using warehousing and cross docking strategies. The supply chain of chemical materials in several European countries has been used as a case study in the article. Nasiri et al. [10] studied the integrated production-distribution problem by considering stochastic demands. They considered a three-echelon supply chain including a number of suppliers, production centers, and distribution centers. They employed a hierarchical approach to determine the production-distribution plans for a one-year time horizon. Marchetti et al. [11] investigated an integrated production-distribution problem to determine the optimal polices in a gas supply chain. The problem was regarded as a multi-period mixed-integer linear programming model to minimize production and distribution costs. Sy [12] investigated the production-distribution problem in a hybrid system in which products are transferred from top level to bottom level and vice versa to reduce the bullwhip effect in the supply chain. Devapriya et al. [13] considered perishable items to investigate the integration of production and distribution scheduling. Given different features of perishable products in previous studies, the lifetime of items was regarded as a criterion for making decisions.

Li and Wang [14] examine a centralized production/distribution system. The objective is to develop an integrated policy that mitigates the negative effects of inventory inaccuracy. Roostaie and Nakhai Kamal Abadi [15] focused on the integrated decision-making process for production, routing, and inventory in a two-echelon supply chain. They addressed the inventory routing problem, where the supplier manages inventory replenishment, delivery timing, quantity, and customer sequence and a heuristic method to overcome the complexity of the problem is considered by them. Izadi et al. [16] studied an integrated production scheduling, vehicle routing, inventory, and outsourcing problem. They developed a model using Mixed Integer Linear Programming (MILP) to minimize total costs. They combined dominance properties with a Genetic Algorithm (GA) to solve the problem. The proposed hybrid algorithm was evaluated through a computational study using randomly generated instances. Azami and Saidi-Mehrabad [17] developed a new multi-period production-distribution planning (PDP) model for perishable products in a three-level supply chain including the factories, distribution centers, and retailers. The objective was to maximize the seller's profit while ensuring the optimality of the buyer. In this paper, factors such as price, discounts, and credit terms have been utilized to enhance competitiveness and incentivize customers. Due to the high complexity of the problem, both genetic algorithms and a hierarchical decomposition-based approach have been utilized to solve the problem. Haghshenas et al. [18] proposed a new mathematical model in a three level supply chain considering location, inventory and pricing of products. They consider a new separate and autonomous channel in this model for the sale of Reman products, with the aim of increasing the manufacturer's profitability. Their developed model has been solved in small dimensions using the LINGO software and in larger dimensions with the assistance of genetic algorithm and particle swarm optimization algorithm. Ghomi-Avili et al. [19] presents an integrated production and distribution model that combines Stackelberg competition and Make-to-Order production system, investigating the impact of discounts on chain profits. They used blockchain technology for enhancing transparency in supply chains. A modified algorithm based on smart contract prices is used to solve the model, demonstrating improved performance and increased network efficiency. Simultaneous decision-making of pricing policies and inventory control for perishable items has been examined by Edalatpour et al [20]; two interrelated price-sensitive linear demand functions to consider the possibility of shortage with both budget and warehouse capacity constraints is considered in their study; Furthermore, they incorporate an upper bound for environmental pollution and a lower bound for job opportunities as additional constraints to their proposed mathematical model.

The research literature has extensively investigated the integration of pricing policies and inventory control in various studies. However, there has been a lack of attention or omission of the pricing aspect when considering production-related decisions in conjunction with inventory control. This discrepancy arises due to the inherent differences in decision-making nature between pricing and production/inventory, resulting in increased complexity when integrating multiple decision levels. Thus, this study aims to address this gap by examining the simultaneous decision-making of pricing, production, and inventory control, along with products distribution decisions, is the novelty of this research. Considering these policies for perishable items constitutes another notable feature of this research.

The importance and contributions of this research can be summarized as follows:

a. This study makes a significant contribution to the field of supply chain management by delving into the intricate realm of dynamic pricing strategies in a multi-level supply chain context.

b. One of the main contributions of this research is the development of a novel pricing approach within a multi-product, multi-period problem, which has been relatively overlooked in the existing literature.
c. By introducing this unique pricing model, our research fills a critical research gap and presents a new perspective on dynamic pricing strategies in the context of perishable goods.
d. The findings of this study offer valuable insights into the dynamic pricing practices that can be adopted in a complex three-level supply chain, contributing to the advancement of pricing strategies in the field.
e. Moreover, this research provides practical implications for businesses operating in industries dealing with perishable products, such as food and pharmaceuticals, by offering an optimized approach to pricing decisions and inventory management.

3. MATHEMATICAL MODEL

As mentioned in the preceding section, this study focuses on a multi-period and multi-product production-distribution system with demand that is dependent on price. The assumptions and notations are explained as follows:

1. All of the parameters in the problem are deterministic and pre-determined.
2. The production-distribution problem is investigated in a multi-period multi-product mode with price-dependent demands to maximize profit in a three-echelon supply chain including several manufacturers, distribution centers and retailers.
3. Demand of Each retailer (customer) in each period is represented by $demand_{j_w} = a_{tipj_w} - b_{tipj_w}p_{tp}$, where p_{tp} indicates the price of product p in the period t.
4. The products are perishable and they are instantaneously deteriorated in a constant rate α.
5. Each manufacturer has a number of production lines and each of them is able to produce all the products.
6. The goods are shipped directly from the manufacturer to the distribution centers.
7. The production capacity of each manufacturer is definite and deterministic.
8. Each customer is only supplied by one distribution center.
9. Each distribution center has a number of heterogeneous fleet of vehicles which are different in transportation cost and capacity.
10. The goods are shipped from the distribution centers to the customers based on vehicle routing problem.
11. Split delivery of products is permitted.
12. Backlog is not permitted.

3. 1. Problem Formulation

In this section, we first provide the notations and definitions used in the current formulation, followed by the introduction of the mathematical formulation.

Sets and indices	
t	Index that represents time periods $t \in \{1,2,\dots,T\}$
i	Index that represents manufacturers $i \in \{1,2,\dots,I\}$
w	Index that represents warehouses $w \in \{1,2,\dots,W\}$
j_w	Index that represents Set of customers of warehouse w; $j_w \in \{1,2,\dots,J_W\}$
N_w	Total number of customers of warehouse w
p	Index that represents products $p \in \{1,2,\dots,P\}$
l	Index that represents production lines for each manufacturer $l \in \{1,2,\dots,L\}$
v_i	Index that represents Sets vehicles of manufacturer i ; $v_i \in \{1,2,\dots,V_I\}$
vw_w	Index that represents vehicles of warehouse w; $vw_w \in \{1,2,\dots,VW_W\}$
Parameters	
F	Fixed cost of production
a_{tipj_w}	Intercept value of demand function of customer j_w in period t
b_{tipj_w}	Slope of the demand function of customer j_w in period t
$c_{v,i}$	Unit transportation cost of vehicle v of manufacturer i
H_{1i}	Unit holding cost of products at manufacturer i
$cap_{max}^{l,p,i}$	Maximum production capacity of line l at manufacturer i for product p
$setup_{p,p'}$	Sequence dependent setup time between product p and p'
$Sc_{p,p'}$	Sequence dependent setup cost between product p and p'
$proc_{p,l,i}$	Processing time of product p in line l of manufacturer i
$PC_{p,l,i}$	Unit cost of product p in line l of manufacturer i
λ_p	Unit volume of product p
w_p	Unit weight of product p
vol_{v_i}	Volume Capacity of vehicle v of manufacturer i
wei_{v_i}	Weight capacity of vehicle v of manufacturer i
Inv_{min}	Minimum inventory level for manufacturer and warehouses
$cv_{(vw_w)}$	Unit transportation cost of vehicle vw of warehouse w
H_{2w}	Unit holding cost of products at warehouse w
vol_{vw}	Volume Capacity of vehicle vw of warehouse w

wei_{vw}	Weight capacity of vehicle vw of warehouse w
c_{perish}	Perishable unit cost
α	Deterioration rate
Decision Variables	
p_{tp}	Price of product p at period t
$pr_{t,p,l,i}$	Amount of product p which assigned to line l of manufacturer i at period t
$Inv_{t,p,i}$	Inventory level of product p at manufacturer i at time t
$Iw_{t,p,w}$	Inventory level of product p at warehouse w at time t
$z_{t(vw_w)m,n}$	Binary variable denoting that if vehicle vw of warehouse w exactly visit node m after node n
$q_{vw_w,m,t}$	Total number of visiting nodes m by vehicle vw of warehouse w at time t
$x_{t,p,w,l,i}$	Binary variable denoting that product p produced by line l for warehouse w at time t
$y_{p,p',l,i}$	Binary variable denoting that product p is processed before p' in line l of manufacturer i
$seq_{p,p',l,i}$	Variable determining that product p is processed right before p' in line l of manufacturer i
$VU_{t,p,v_i,i,w}$	Amount of product p shipped from manufacturer i to warehouse w at time t by vehicle v_i
VL_{t,j_w,p,vw_w}	Amount of product p shipped from warehouse w to customer j_w at time t by vehicle vw_w

The mathematical model of the integrated production-distribution problem is presented as follows:

$$Min \sum_{t,i,j_w}\left(a_{tipj_w}p_{tip} - b_{tipj_w}p_{tip}^2\right) -[F + \sum_{t,p,p',l,i} pr_{t,p,l,i}.PC_{p,l,i} + \sum_{t,p,p',l,i} seq_{t,p,p',l,i}.Sc_{p,p'} + \sum_{v,i,w} c_{v,i}.d_{iw}.zz_{tv_iiw} + \sum_{t,p,i} H_{1i}.Inv_{t,p,i} + \sum_{t,p,w} H_{2w}.Iw_{t,p,w} + \sum_{t,w,j_w,(vw_w),m,n} d_{wj_w}.cv_{(vw_w)}.z_{t(vw_w)m,n} + \sum_{t,w,p,(vw),j_w} \pi_{t,p,(vw_w),j_w}B_{t,p,vw_w,j_w} + \sum_{t,p} c_{perish}.\alpha.\left(Inv_{t,p,i} + Iw_{t,p,w}\right) \quad (1)$$

$s.t.$

$$\sum_{l,i} x_{t,p,w,l,i} = 1 \ \forall t,p,w \quad (2)$$

$$\sum_{l,i} pr_{t,p,l,i} \leq cap_{max}^{l,p}.x_{t,p,w,l,i} \ \forall t,p,w \quad (3)$$

$$start_{t,p',l,i} \geq finish_{t,p,l,i} + setup_{p,p'}.seq_{t,p,p',l,i} - M.\left(1 - y_{p,p',l,i}\right) \ \forall t,p,p',l,i \quad (4)$$

$$finish_{t,p,l,i} \geq start_{t,p,l,i} + pr_{t,p,l,i}.proc_{p,l,i} \quad \forall t,p,p',l,i \quad (5)$$

$$y_{t,p,p',l,i} + y_{t,p',p,l,i} \geq x_{t,p,w,l,i} + x_{t,p',w,l,i} - 1 \quad \forall t,p,p',l,i,w \quad (6)$$

$$y_{t,p,p',l,i} \leq x_{t,p,w,l,i} \quad \forall t,p,p',l,i,w \quad (7)$$

$$y_{t,p',p,l,i} \leq x_{t,p',w,l,i} \ \forall t,p,p',l,i,w \quad (8)$$

$$pos_{t,p,p',l,i} = \sum_{(p,p')\neq p''}\left(y_{t,p,p'',l,i} - y_{t,p,p',l,i}\right) + M.\left(1 - y_{t,p,p',l,i}\right) \forall t,p,p',p'',l,i \quad (9)$$

$$pos_{t,p,p',l,i} + seq_{t,p,p',l,i} \geq 1 \quad \forall t,p,p',l,i \quad (10)$$

$$\sum_{t,w} zz_{tv_iiw} \leq 1 \quad \forall i,v_i \quad (11)$$

$$\sum_p \lambda_p VU_{t,p,v_i,i,w} \leq zz_{tv_iiw}.vol_{v_i} \quad \forall t,v_i,i \quad (12)$$

$$\sum_p w_p VU_{t,p,v_i,i,w} \leq zz_{tv_iiw}.wei_{v_i} \quad \forall t,v_i,i \quad (13)$$

$$\sum_p \lambda_p VU_{t,p,v_i,i,w} \leq vol_{v_i} \quad \forall t,v_i,i \quad (14)$$

$$\sum_p w_p VU_{t,p,v_i,i,w} \leq wei_{v_i} \quad \forall t,v_i,i \quad (15)$$

$$Inv_{t,p,i} = Inv_{t-1,p,i}(1-\alpha) + \sum_l pr_{t,p,l,i} - \sum_{v_i,w} zz_{tv_iiw}.VU_{t,p,v_i,i,w} \quad \forall t,p,i \quad (16)$$

$$Inv_{t,p,i} \geq Inv_{min} \quad \forall t,p,i \quad (17)$$

$$Iw_{t,p,w} \geq Iw_{min} \quad (18)$$

$$Iw_{t,p,w} = Iw_{t-1,p,w}(1-\alpha) + \sum_{v_i,i} VU_{t,p,v_i,i,w} - \sum_{vw_w,j_w} VL_{t,j_w,p,vw_w} \forall t,p,w \quad (19)$$

$$\sum_{v_i,i} VU_{t,p,v_i,i,w} \geq \sum_{vw_w,j_w} VL_{t,j_w,p,vw_w} \quad \forall t,p,w \quad (20)$$

$$\sum_{vw_w} z_{t(vw_w)m,n} \geq 1 \ \forall t,w,m,n \quad (21)$$

$$\sum_m z_{t(vw_w)m,n} = \sum_n z_{t(vw_w)n,m} \quad \forall t,w \quad (22)$$

$$q_{vw_w,m,t} - q_{vw_w,n,t} + (N_w + 1).z_{t(vw_w)m,n} \leq N_w \quad \forall t,w \quad (23)$$

$$\sum_{vw_w} VL_{t,j_w,p,vw_w}.z_{t(vw_w)m,n} = a_{tipj_w} - b_{tipj_w}p_{tp} \quad \forall t,w,p,j_w \quad (24)$$

$$\sum_{p,j_w} \lambda_p VL_{t,j_w,p,vw_w} \leq vol_{vw} \quad \forall t,w \quad (25)$$

$$\sum_{p,j_w} w_p VL_{t,j_w,p,vw_w} \leq wei_{vw} \quad \forall t,w \quad (26)$$

$$x_{t,p,w,l,i} \in \{0,1\}; y_{p,p',l,i} \in \{0,1\}; seq_{p,p',l,i} \in \{0,1\}; \quad z_{t(vw_w)m,n} \in \{0,1\} \quad BC_{t,j_w} \in \{0,1\}; p_{tp} \geq 0; pr_{t,p,l,i} \geq 0; Inv_{t,p,i} \geq 0; Iw_{t,p,w} \geq 0; \quad VU_{t,p,v_i,i,w} \geq 0;\ VL_{t,j_w,p,vw_w} \geq 0 \quad (27\text{-}37)$$

Equation (1) represents the maximization of the manufacturer's net profit, calculated as the total revenue minus the sum of the total cost. Equation (2) states that a warehouse-related product known as a product order, can only be allocated to one production line in each period. Constraint (3) ensures that the amount of production on a production line within a production center does not exceed its capacity. Constraints (4) and (5) determine the start and finish times of different production batches. The production sequence of two batches is determined by Constraints (6-10). For each period, each vehicle is assigned to transport goods from one production center to one warehouse; These constraints are expressed in Equations (11) to (13). Constraints (14) and (15) impose limitations on the total products shipped from each manufacturer to each warehouse, ensuring that they do not exceed the maximum weight and volume capacity of the vehicles. Equations (16-19) specify the inventory levels of different products in the manufacturing warehouses and distribution centers. In equation (16), the term $Iw_{t-1,p,w}(1-\alpha)$ shows that the items which are non-deteriorated will be received from previous period. The quantity of products received from each warehouse should be greater than or equal to that of products sent by the warehouse which is ensured by Constraint (20). Equation (21) states the condition under which each customer can be visited by the vehicles more than once. Consecutive movements of vehicles are stated by Constraint (22); this means that every vehicle should exit a node after entering it. Equation (23) is a subtour elimination constraint. Equation (24) guarantees that total number of delivered products to each customer should be equal to its demand. Constraints (25) and (26) are similar to Constraints (14) and (15) but they relate to distribution centers. The domains of the decision variables are set by Constraints (27) to (37).

4. PROPOSED GENETIC ALGORITHM

Evolutionary algorithms (EAs) depict the simulation of nature process to invent the metaheuristic algorithm [21]. Genetic algorithm is one of the most effective search methods which have been successfully applied to many combinatorial optimization problems in which the regeneration process of living beings is simulated for solving complicated problems in different areas of science and engineering. It is a type of evolutionary algorithm that utilizes biological processes like inheritance, biology mutation, and Darwin's selection principles to find the optimal solution [21]. GAs are the special type of EAs and include so many methods in this classification. Chromosomes are the structure of cells in animals, plants and humans. In GA, we define an array of variables which is called chromosome. Chromosomes are altered by two operators: mutation and crossover; The types of two mentioned operators are addressed by several recent studies [22]. The framework proposed in this research for implementation of the genetic algorithm will be described in the following subsection. Each step of implementing the algorithm will be outlined below:

1. Generating the initial population randomly;
2. Calculating the fitness functions of the chromosomes;
3. Selecting parents for creation of the next generation;
4. Applying the crossover and mutation operators;
5. Updating the population;
6. Iterating Steps 2-6 until the termination condition is met (determining the number of iterations);

4. 1. Representation The solution vector representation in every EA should be as compact as possible but should contain enough information to represent any solution of the problem. The way of representing solutions significantly affect the choice of searching operators. Accordingly, efficient representation of the solutions helps to use well-known operators in the literature that their high performance has been proved [23]. In this paper, a hybrid chromosome representation is utilized to represent the chromosomes in each generation. Considering that each customer's demand in each period is price-dependent, initially the price of each product in each period is generated randomly in range $[p_{tp}^U, p_{tp}^L]$ where p_{tp}^U and p_{tp}^L are the upper and lower bound for the price of product p in period t and it will be determined as follows. As mentioned in previous section, demand of each customer is price-dependent and considered as: $demand_{j_w} = a_{tipj_w} - b_{tipj_w} p_{tp}$ which is simply a linear function. We assume that the price of a product is the same for all customers but may change during different periods. The primary condition to determine the acceptable range of the price for each product will be determined by solving the following inequality:

$$a_{tpj_w} - b_{tpj_w} p_{tp} \geq d_{tpj_w}^{min} \tag{38}$$

Consequently, for each customer we have:

$$p_{tp} \leq \frac{a_{tipj_w} - d_{tpj_w}^{min}}{b_{tipj_w}} \qquad \forall w, j \tag{39}$$

Thus, considering above results will determine the upper bound for price of each product in each period as follows:

$$p_{tp}^u = Min\{p_{tp}\} = \underset{w,j}{Min}\left\{\frac{a_{tpj_w} - d_{tpj_w}^{min}}{b_{tpj_w}}\right\} \tag{40}$$

Now, suppose that maximum demand of each customer is represented by $d_{tpj_w}^{max}$; therefore, we have:

$$a_{tpj_w} - b_{tpj_w} p_{tp} \leq d_{tpj_w}^{max} \tag{41}$$

And thus:

$$p_{tp} \geq \frac{a_{tipj_w} - d_{tpj_w}^{max}}{b_{tipj_w}} \qquad \forall w, j \tag{42}$$

Based on the aforementioned results, the lower bound for the price of each product in each period can be determined as follows:

$$p_{tp}^l = Max\{p_{tp}\} = \underset{w,j}{Max}\left\{\frac{a_{tipj_w} - d_{tpj_w}^{max}}{b_{tpj_w}}\right\} \tag{43}$$

Now, we can present the proposed chromosome structure of the problem. In this study, to describe a solution to the problem, a mixed representation is utilized in which each chromosome includes four sections.

For example, assume that the production-distribution problem is to be designed for the bi-product mode with four time periods. Figure 1(a) indicates the first section of the hybrid chromosome structure namely pricing sub-chromosome.

The demand of each customer for each product is determined based on the specified price structure. For example, the demand for the first product from all customers is set at a price of 35 in the first period, while for the second product it is set at a price of 28 in the second period. This process is repeated for each period and customer, ensuring that the demand is aligned with the corresponding price. Each customer's demand for each product in each period will be determined by having the price specification. Therefore, it is necessary to specify the number of products shipped to each customer by each vehicle. Furthermore, visiting different customers should be arranged for every vehicle. Assume that there are two warehouses, the first one with five customers and the second one with three customers. It means that there are 8 customers among which customers 6-8 represent those of the second warehouse and if there are more customers then they will be numbered in the same way. In each period, one vehicle is selected randomly for each warehouse. Then, the order of customers' visits is randomly generated (it should be noted that each vehicle starts at and ends in a warehouse; however, it is not represented in the chromosome structure). Figure 1(b) shows the order of visits of the different customers in four time periods.

Now, the selected vehicle can ship all the customer demand. After each gene is filled, a part of the weight and size capacity of the vehicle is occupied which should be considered when the next genes are in action. If the weight or volume capacity of the vehicle is reached, any remaining customers will be assigned to another vehicle (the order of remaining customers can be considered in the same way as the order of vehicles, or a new order can be established). Figure 1(c) shows the quantity of products shipments to customers in each period. For example, 45, 20, and 30 units of the first, second, and third product respectively are sent to customer 2 in the first period.

Based on the quantity of goods transported by the vehicles from each warehouse to the customers, and taking into account the minimum inventory requirements for each product, the total demand for each product is calculated. Now, the production of these products needs to be scheduled in the production lines of the manufacturer. For example, let's consider two production centers, each equipped with two production lines, where each line has a maximum production capacity. Figure 1(d) shows the structure used to determine the production order of a product in the production centers. The first number indicates the product, the second represents the warehouse, the third refers to the production line, and the fourth indicates the manufacturer.

Now, a population of chromosomes is generated according to the described structure and based on the size of the population.

4. 2. Determining the Fitness Function The fitness function of each chromosome is calculated once the initial population is generated. In this study, only feasible chromosomes are generated, and therefore the objective function is used directly as the fitness function.

4. 3. Selection The process of parent selection is carried out to generate a new generation within the current population. The genetic operators (crossover and mutation) are then applied to produce the new generation; Since the population size is fixed, a certain number of chromosomes are removed from the current population based on the fitness function. Although there are various methods available for selection of parents from the population to produce the generation, some methods may decrease the likelihood of producing high-quality offspring from parents with unfavorable fitness values by favoring the best fitness functions and selecting the best parents. Among different selection methods, the roulette wheel technique is a method in which each chromosome has the chance of being selected. Therefore, the roulette wheel method was used according to the rules described below:

1. $F'(ch) = F_{max} - F(ch)$

a Pricing sub-chromosome

35	24	28	31
26.4	28	30	18

b Vehicle Routing Sub-chromosome

2	4	1	3	5	8	6	7
1	3	2	4	5	6	7	8
4	2	5	1	3	6	7	8
3	4	5	2	1	7	6	8

c Sub-chromosome of distribution quantity of products for customers

45-20-30	30-20-15	50-45-20	15-25-20	60-30-20	25-40-18	30-20-40	30-25-15
25-20-30	10-40-20	30-35-25	20-45-30	25-25-25	30-20-15	40-25-30	15-20-40
35-28-50	25-22-48	35-20-45	20-30-50	15-10-30	25-30-45	22-38-40	24-10-5
15-25-20	20-15-35	30-42-24	18-32-16	30-19-45	18-25-20	35-30-22	24-15-20

Assignment of demand of warehouses to production lines of manufacturer

d

2211	3221	2121	3122	1111	1211

Figure 1. An example of chromosome encoding

2. $RW(ch) = \frac{\sum_{i=1}^{i=ch} F(i)}{\sum_{j=1}^{pop\_size} F\prime(j)}$
3. $Generate\ a\ random\ number\ between\ 0\ and\ 1:$
4. $If\ RW(ch-1) < rand \leq RW(ch)\ \ and\ RW(0) = 0\ \ then\ \ select\ chromosome\ ch$

4. 4. Crossover Crossover operator is used to diversify the search process. In this study, the crossover operator will be applied to two selected chromosomes from the population. The process will be described in the following section.

I. *Generate a random number R_1 between 0 and 1, if $R_1 \leq \eta$ go to step II and go to step III otherwise;*
II. *Apply crossover operator to vehicle routing sub-chromosome;*
III. *Apply crossover operator to production sub-chromosome;*

η is the probability that shows whether the crossover operator should be applied to vehicle routing sub-chromosome or production sub-chromosome.

An example of crossover operator is as follows. In each period, a number of genes are randomly selected from the first parent and transferred to the first offspring. Then, the genes of the second parent are compared with the genes transferred to the first child from left to right, and are transferred to the first empty gene in the case of absence. In the first period of the first offspring, for instance, the second parent is considered after genes 4-1-3 of the first parent are transferred. The value of the first gene is 3 which belongs to the first child and accordingly skipped to the next gene. The value of the second gene is 2 which is put into the first empty gene because 2 is not involved with the first child. The next value is 5 which is put into the next empty gene that will be in the first child and finally, 4 is inserted. The procedure is repeated for the second period. The genes selected from the first parent are shown in yellow which are seen in the same order and color in the first child. The same procedure is repeated with regard to the second child; however, the genes are selected from the second parent. Figure 2 shows the proposed crossover operator for vehicle routing sub-chromosome. The crossover operator can be utilized to allocate lots to the production lines. In this case, for the first offspring, certain genes are randomly selected from the first parent and transferred to the first offspring. Then, the genes of the second parent are compared with the genes transferred to the first child, and any remaining empty genes are filled with the corresponding genes from the second parent. This crossover process follows the same principles as the crossover operator used in previous sub-chromosomes. This process is shown in Figure 3.

For the second child, a number of genes are selected from the second parent. It should be noted that only the first two numbers, representing the product and warehouse, are considered in comparison with the genes of a parent with the filled genes of each offspring.

3. 5. Mutation After the crossover operator, the mutation operator is applied to explore portions of the solution space that may not be accessible through the crossover operation alone. Typically, the mutation operator is applied to individual chromosomes. In this study, the mutation operator is defined as follows:

I. *Generate a random number R_2 between 0 and 1, if $R_1 \leq \lambda$ go to step II and go to step III otherwise;*
II. *Apply mutation operator to vehicle routing sub-chromosome;*
III. *Apply mutation operator to production sub-chromosome;*

λ is the probability that shows whether the mutation operator should be applied to vehicle routing sub-chromosome or production sub-chromosome.

Two genes are selected in each period which are then replaced with each other. Figure 4 shows the mutation operator used for the current study.

4. COMPUTATIONAL RESULTS

In this section, computational results of the proposed genetic algorithm are presented. The generation of instances is described in section 5.1 while the parameters of proposed genetic algorithm are presented in section 5.2; This section is dedicated to discussing the numerical results.

Due to the high complexity of the research problem and the difficulty in obtaining optimal solutions, even in small-sized problems is difficult therefore 2 simple test problems, each of them consists of 9 sub-problems, are first solved by BARON solver of GAMS software. The results are then compared with those obtained from the GA, which has been implemented in C#. After confirming the efficiency of the designed genetic

First parent	2	4	1	3	5	8	6	7
	1	3	2	4	5	6	7	8
	4	2	5	1	3	6	7	8
	3	4	5	2	1	7	6	8
Second parent	3	2	5	1	4	7	6	8
	5	1	2	3	4	6	7	8
	1	2	3	4	5	8	6	7
	2	3	1	5	4	8	6	7
First offspring	2	4	1	3	5	8	6	7
	1	3	5	2	4	6	7	8
	2	4	5	1	3	6	7	8
	3	1	5	2	4	6	7	8

Figure 2. An example of crossover operator for Vehicle Routing Sub-chromosome

2211	3221	2121	3122	1111	1211
1121	2112	2222	3211	1221	3112
1121	3221	2121	3122	2222	1221

Figure 3. Crossover operator for two warehouses and three products

algorithm, five problems, each with nine sub-problems, are solved using the genetic algorithm.

5. 2. Generation of Instances Problem instances have been generated and divided into two groups: test and main problems where there are 9 instances in each group as shown in Table 1.

The values of the parameters are shown in Table 2. Given the fact that the parameters of metaheuristic algorithms have great impact on the convergence and good performance of the algorithm, therefore a variety of combination of parameter values have been tested in order to set the GA parameters. Experimental results have shown that the following values can obtain satisfactory results and therefore are used for all examples: population size=100, crossover probability=0.8, $\eta = 0.7$, mutation Probability=0.3, $\lambda = 0.45$ and Maximum number of iterations=1500.

5. 2. Results In this section, numerical results on the performance of the proposed genetic algorithm are presented. All of the sample problems were coded in GAMS24.7.4 and C# executed on a computer operating system with a Core i5 processor and 8 GB of RAM. The genetic algorithm was executed 10 times on each sample problem; Numerical reports were generated for the average, best, and worst solutions obtained, along with the standard deviation of the objective function across the

parent	2	4	1	3	5	8	6	7
	1	3	2	4	5	6	7	8
	4	2	5	1	3	6	7	8
	3	4	5	2	1	7	6	8
offspring	2	5	1	3	4	6	8	7
	3	1	2	4	5	7	6	8
	3	2	5	1	4	6	8	7
	2	4	5	3	1	8	6	7

Figure 4. Mutation operator

TABLE 1. Problem instances

	A	B	C	D	E	F	G 1	G 2	H 1	H 2
Test problems	1	1	1	5	3	3	2	4	2	4
	2	1	2	5	3	3	2	4	2	4
Main problems	1	2	2	4	3	3	2	4	2	4
	2	2	3	6	5	4	2	4	2	4
	3	2	4	8	7	5	2	4	2	4
	4	2	5	15	10	6	2	4	2	4
	5	2	6	20	10	7	2	4	2	4

A: Problem No. B: No. of manufacturer; C: No. of Distribution Centers; D: No. of customers of each DCs; E: No. of Vehicles of manufacturer; F: No. of Vehicles of each DC; G: No. of Products; H: Time periods;
1: Min and 2: Max

TABLE 2. The values of parameters

Parameter	**Value**	**Parameter**	**Value**
a_{tipj_w}	$U[50,100]$	b_{tipj_w}	$U[1,1.5]$
$F, c_{v,i}, cv_{(vw_w)}, \pi_{t,p,(vw_w),j_w}, c_{perish}$	1	α, β	0.1
$cap_{max}^{l,p,i}$	$3.5N \sum_{t,i,j_w}(a_{tipj_w} - b_{tipj_w} p_{tip})$	$setup_{p,p'}$	$U[0.1,0.5]$
$Sc_{p,p'}$	$U[0.1,0.5]$	$proc_{p,l,i}$	0.1
$PC_{p,l,i}$	$U[4,6]$	λ_p	$U[0.1,1]$
w_p	$U[2,5]$	vol_{v_i}	$U[300,400]$
wei_{v_i}	$U[1000,1500]$	Inv_{min}	$U[20,30]$

10 runs and the obtained results were reported in the table of results. Tables 3-5 show the computational results of solving different sample problems. According to Tables 3-5, it is obvious that the proposed genetic algorithm is efficient as the average gap between the solutions provided by the genetic algorithm and the optimal ones is 1.6% for the first test problem and 3.3% for the second test problem which demonstrates that the solutions to the medium and large sample problems can be trusted. Comparison of the performance of the genetic algorithm with the optimal solution of the problem for two cases, as shown in Figures 5 and 6, respectively. Table 6 shows the computational results for Main problems which have been solved by genetic algorithm.

Considering the importance of the price parameter and its significant impact on management policies, Table 5 reports the obtained price values solely for the first test problem at different periods. As observed, the obtained prices have very minor differences compared to the values reported by the BARON algorithm, indicating the effectiveness of the proposed algorithm in solving the problems.

The outcomes achieved by applying the Genetic Algorithm to two experimental problems validate the robustness of the algorithm's evolutionary framework. Thus, we can exclusively employ the proposed Genetic Algorithm to solve the primary problems and confidently utilize the obtained solutions. Table 6 provides the solution outcomes for 5 main problems, each comprising 9 subproblems, encompassing the objective function values and the corresponding solution times.

The development of the multi-objective formulation and the utilization of hybrid multi-objective evolutionary algorithms (HMOEAs), the incorporation of novel approaches in genetic algorithms or using state-of-the-art algorithms such as NGO or SEO algorithms and integration of deep learning and machine learning techniques for future research are suggested as highly intriguing topics[24-29].

TABLE 3. Objective function of first test problem and CPU time

	BARON				Genetic algorithm				
Prob. No.	**Constraints**	**Variables**	**Objective function**	**Time (s)**	**(Best)**	**(Average)**	**(Worst)**	**Time (s)**	**Standard Deviation**
1	409	353	51689.41	205.2	52018.21	52083.73	52102.72	1.86	36.20
2	613	525	83032.27	398.12	85921.287	86482.19	87157.62	2.1	505.45
3	817	697	111817.65	221.5	113501.67	113968.02	114727.21	2.43	505.06
4	555	459	80258.12	119.1	81981.34	82476.98	83022.54	2.99	425.23
5	832	679	146867.34	276.4	148156.18	149002.42	150202.77	4.76	839.67
6	1109	899	167429.57	548.23	169218.561	169460.33	169813.49	11.21	244.29
7	757	585	115712.27	432.8	118721.16	119276.44	120019.27	4.01	531.79
8	1135	861	172046.19	542.1	174281.786	174822.36	175113.52	6.89	344.60
9	1513	1137	264293.38	845.8	266716.187	267392.01	268347.31	26.91	669.15

TABLE 4. Objective function of second test problem and CPU time

	BARON				Genetic algorithm				
Prob. No.	**Constraints**	**Variables**	**Objective function**	**Time (s)**	**(Best)**	**(Average)**	**(Worst)**	**Time (s)**	**Standard Deviation**
1	601	417	88382.16	867.2	89219.432	89967.296	91056.06	11.3	781.23
2	901	621	115371.07	971.3	117376.19	118257.86	119714.26	21.7	943.35
3	1201	825	166815.34	826.1	171572.189	171874.34	172113.60	38.87	248.02
4	817	529	114107.56	1421.3	118671.102	119965.32	121258.74	49.16	1081.12
5	1225	784	173317.86	602.1	182098.17	182098.17	182625.82	80.9	253.24
6	1633	1039	230168.25	1034.4	236715.74	236715.74	239101.23	121.54	1113.21
7	1113	661	166749.43	897.3	172786.17	172786.17	173429.94	76.91	321.78
8	1669	975	205753.12	926.12	208761.65	208761.65	212495.47	110.17	1746.17
9	2225	1289	325720.388	5892.1	351023.512	351023.512	355372.72	132.78	2081.62

TABLE 5. Obtained price for sub-problems of the first sample problem

Problem No.	**Time Period**	**Product 1**		**Product 2**		**Product 3**		**Product 4**	
		BARON	**GA**	**BARON**	**GA**	**BARON**	**GA**	**BARON**	**GA**
1	1	64	63.03	77	76.82				
	2	61	62.17	61	59.43				
2	1	80	80.24	78	79.32				
	2	84	83.96	72	71.43				
	3	63	63	72	72.23				
3	1	76	75.42	69	69.94				
	2	64	64.7	70	69.63				
	3	61	60.67	61	62.01				
	4	62	61.9	61	61				
4	1	66	65	61	61.1	63	61.76		
	2	64	64.85	97	97.67	67	67.39		

5	1	84	84.06	79	78.3	79	78.12		
	2	66	67.57	73	73.16	70	69.12		
	3	66	67.9	64	63.9	64	64.16		
6	1	65	64.38	64	62.89	65	65.19		
	2	67	67.11	70	71.01	63	63.12		
	3	61	59.81	65	64.38	66	66.15		
	4	60	59.19	56	55.61	56	55.81		
7	1	55	54.1	61	60.14	55	54.9	56	55.71
	2	66	66.09	67	67.09	66	67.01	66	67.1
8	1	68	67.21	69	69.18	67	68.19	67	66.64
	2	59	58.32	60	60.21	59	58.41	59	59.7
	3	64	63.01	62	61.67	62	61.78	62	61.1
9	1	98	99.78	90	92	82	83	81	79.12
	2	79	81	66	66.12	74	74.3	73	72.67
	3	64	63.9	85	85.62	85	86.01	85	84.18
	4	68	68.14	70	70.15	70	70.91	70	70.1

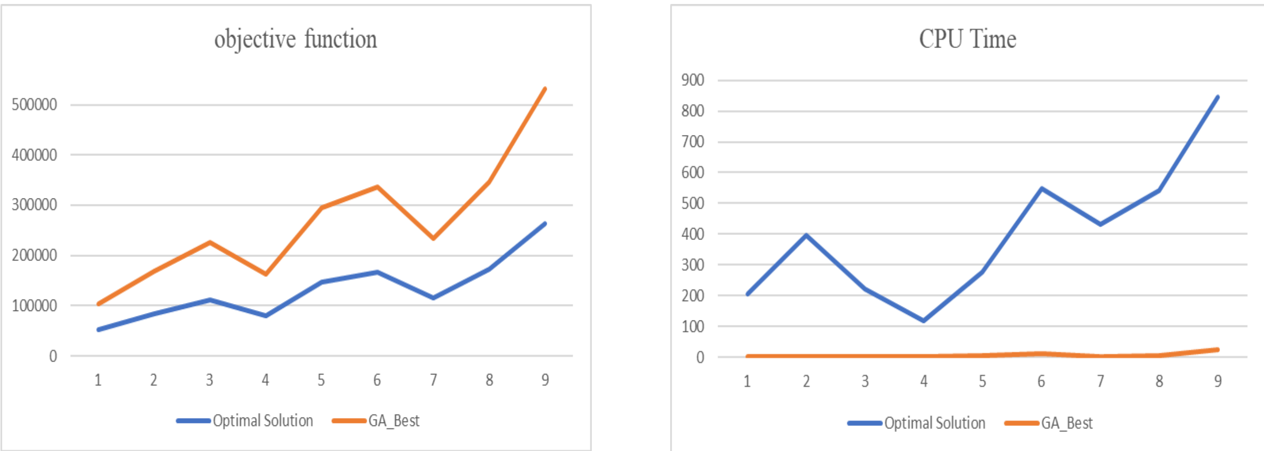

Figure 5. Optimal solution VS best reported value by the genetic algorithm for the first test problems

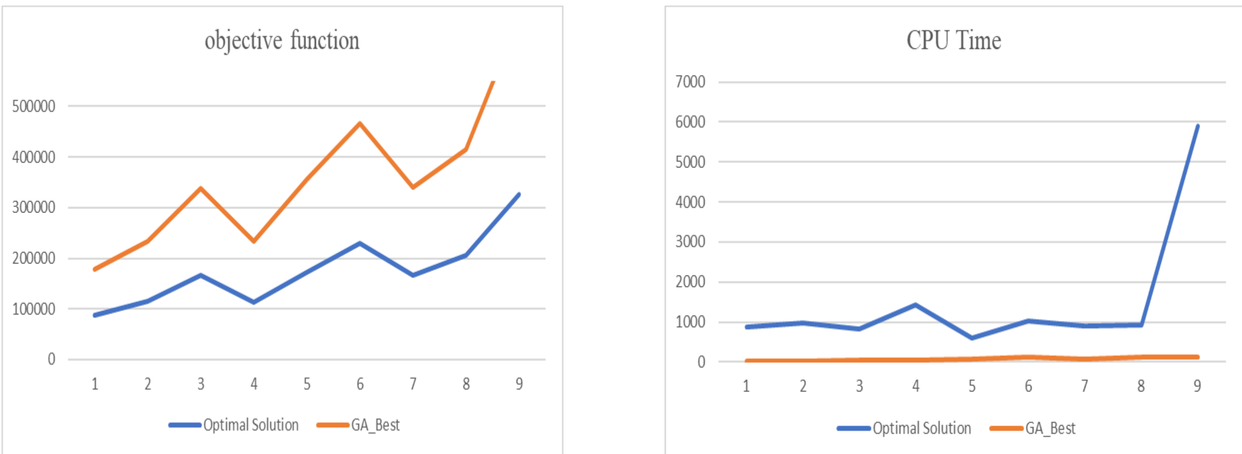

Figure 6. Optimal solution VS best reported value by the genetic algorithm for the second test problems

TABLE 6. Objective function of main problems with CPU time

Sub-problem	1-1	1-2	1-3	1-4	1-5	1-6	1-7	1-8	1-9
Obj. Fun.	97326.172	136098.016	194738.648	122254.19	188097.143	217943.92	177218.176	220715.81	257876.12
Time (s)	15.2	22.1	24.7	36.5	42.7	78.9	72.2	93.6	105.4
Sub-problem	**2-1**	**2-2**	**2-3**	**2-4**	**2-5**	**2-6**	**2-7**	**2-8**	**2-9**
Obj. Fun.	632.118745	308.140392	619.200593	678.131056	191267.7	63.232645	190678.732	228765.32	156.265328
Time (s)	6.17	2.23	56.39	5.52	3.84	3.126	4.86	7.117	1.138
Sub-problem	**3-1**	**3-2**	**3-3**	**3-4**	**3-5**	**3-6**	**3-7**	**3-8**	**3-9**
Obj. Fun.	316.142089	217.175456	18.237651	278.162345	76.209867	26.269017	86.193796	278.254871	112.304768
Time (s)	2.23	9.28	4.46	3.61	3.89	2.134	7.96	22.126	3.148
Sub-problem	**4-1**	**4-2**	**4-3**	**4-4**	**4-5**	**4-6**	**4-7**	**4-8**	**4-9**
Obj. Fun.	027.194219	706.227691	064.271237	786.222612	723.285675	717.316234	2.269432	367.300492	212.364765
Time (s)	1.28	6.34	32.52	9.83	4.102	45.156	32.116	4.138	2.167
Sub-problem	**5-1**	**5-2**	**5-3**	**5-4**	**5-5**	**5-6**	**5-7**	**5-8**	**5-9**
Obj. Fun.	067.238543	167.291324	634.338178	154.28821	475.323423	098.37232	965.319869	991.363567	675.410025
Time (s)	3.41	8.58	3.72	6.116	2.141	9.175	2.132	3.163	8.193

6. CONCLUSION, FINDINGS, LIMITATION AND FUTURE DIRECTIONS

This paper investigates an integrated multi-product and multi-period production-distribution system involving multiple manufacturers, distribution centers, and customers. The system considers split delivery and focuses on delivering perishable goods without allowing shortages. Since limited research has focused on pricing in production-distribution systems, this study proposes a mathematical formulation to maximize profit by incorporating dynamic pricing policies, which serves as a significant contribution of the study. Due to the high complexity of the developed mathematical model, a genetic algorithm is employed as an appropriate tool for solving the problem instances. Additionally, a set of test problems is initially solved to achieve optimality, and the efficiency of the proposed genetic algorithm is evaluated by comparing its results with the optimal solutions. Considering the effective performance of the genetic algorithm on the test problems, the main problems are also solved using the genetic algorithm, resulting in near-optimal or optimal solutions. Advanced optimization algorithms have proven their effectiveness in multiple domains, including online learning, scheduling, multi-objective optimization, transportation, medicine, and data classification. Their success in these areas demonstrates their potential for various decision-making problems, extending beyond the specific focus of this study. These algorithms offer valuable tools for decision-making across different contexts and present opportunities for enhancing problem-solving capabilities.

In the following, the most significant findings of the research and the limitations associated with conducting this study will be described.

In this research, all the parameters of the problem have been assumed to be deterministic, while in the case of parameters such as demand, it is not easy to assume certainty, as we always expect fluctuations in product demand. On the other hand, the price of a product is influenced by numerous factors, many of which have not been considered in this study. All of these factors are simply disregarded to prevent increasing the complexity of the mathematical model.

The solution of an integrated model that addresses production planning and scheduling, inventory control, routing and distribution, and ultimately pricing of products over multiple periods is the most significant finding of the research. Future researchers can propose better and stronger approaches to solving the problem and dealing with its inherent complexities by taking a closer look at this issue. Another limitation inherent in this study is the failure to empirically implement the findings derived from the mathematical model within a practical context; It is imperative that future research endeavors involve the application of the developed model to a real-world problem, thereby facilitating a comprehensive analysis of the results.

The research contributes to the advancement of vehicle scheduling in warehouses and cross-docking operations. In addition, it would be interesting to consider reverse logistics in the mathematical model. Given that the genetic algorithm was only used for the problems, appropriate approaches to determine upper and lower bounds to control and navigate the genetic algorithm may improve the solutions. Considering the complexity of the problem examined in this research, it appears that employing simulation approaches as an attractive method can be highly effective in achieving high-quality solutions. Furthermore, it presents an intriguing research area for the further development of recent studies

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Persian Abstract

چکیده

اهمیت استفاده از استراتژی‌های قیمت‌گذاری مناسب برای محصولات فاسدشدنی در زنجیره تأمین بیانگر نیاز اساسی است. قیمت‌گذاری به عنوان یک راننده عملکردی مشترک در هر زنجیره تأمین نقشی قاطع در موفقیت و سودآوری زنجیره تأمین را در کنار عوامل دیگری نظیر سیاست‌های موجودی و تولید ایفا می‌کند که در این پژوهش مورد بررسی قرار گرفته‌اند. این پژوهش بر تأکید بر نقش مهم قیمت‌گذاری در سودآوری، همراه با تداخل سیاست‌های تولید و کنترل موجودی، و تأثیر مشترک آنها بر نتایج مالی تمرکز دارد. موضوع قیمت‌گذاری پویا در یک مسئله چندمحصوله و چنددوره‌ای در یک زنجیره تأمین سه سطحی با محصولات فاسدشدنی تاکنون به طور محدود مورد توجه قرار گرفته استاین مطالعه به بررسی قیمت‌گذاری پویا در یک مسئله چند محصولی و چند دوره‌ای در یک زنجیره تأمین سه‌سطحی با محصولات فسادپذیر با تاکید بر نقش مهم قیمت در سودآوری می‌پردازد. سیستم یکپارچه تولید–توزیع مورد مطالعه شامل تولیدکنندگان و مراکز توزیع متعدد است و هر یک از آن‌ها به یک گروه خاص از مشتریان خدمات ارائه می‌دهند. ارسال محصولات بین مراکز تولید و مراکز توزیع بصورت مستقیم و همچنین بین مراکز توزیع و خرده‌فروشان براساس مسئله مسیریابی وسیله نقلیه است. به منظور بیشینه‌سازی تابع هدف، یک مدل برنامه‌ریزی عددصحیح مختلط توسعه یافته و روشی فراابتکاری بر مبنای الگوریتم ژنتیک برای دستیابی به جواب‌های با کیفیت ارائه شده است. به دلیل پیچیدگی بالای مسئله تحقیق(حتی در ابعاد کوچک) حل بهینه مساله به سادگی امکانپذیر نیست، به همین دلیل در ابتدا 2 دسته مسایل آزمایشی ساده که هر کدام شامل نُه زیرمسئله هستند، توسط حل‌کننده BARON نرم‌افزار GAMS حل می‌شوند و نتایج حاصل با نتایج الگوریتم ژنتیک که با زبان سی‌شارپ پیاده‌سازی شده است، مقایسه می‌شوند. پس از تأیید کارآیی الگوریتم ژنتیک طراحی شده، پنج مسئله اصلی با نُه زیرمسئله برای هرکدام، توسط الگوریتم ژنتیک حل شده‌اند.