



A Bi-objective Robust Optimization Model for an Integrated Production-distribution Problem of Perishable Goods with Demand Improvement Strategies: A Case Study

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ABSTRACT

This paper develops a bi-objective optimization model for the integrated production-distribution planning of perishable goods under uncertainty. The first objective seeks to maximize the profit in a specific supply chain with three levels: plants, distribution centers, and in the last level, customers. Since transportation is one of the major pollution sources in a distribution problem, the second objective is to minimize their emission. In the considered problem, the decisions of production, location, inventory, and transportation are made in an integrated structure. In developing the demand function, the effect of the product freshness and the price is formulated. Besides, to encourage customers, three strategies, including perished product return, discount, and credit policies, are proposed. Also, robust optimization is utilized to cope with the operational uncertainty of some cost parameters. To prove the applicability of this research and the feasibility of the environmental aspect, a case study is conducted. Finally, the numerical computations on the case study provide a trade-off between the environmental and economic goals and indicate a 37.5 percent increase in the profit using the developed model.

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1. INTRODUCTION

Production and distribution problems play a vital role in supply chain management [1]. Many companies are seeking to optimize their production and distribution planning (PDP) simultaneously and in an integrated framework to achieve the highest profit as well as the highest satisfaction of customer demand [2]. In this article, the first objective aims to maximize the production and distribution (P-D) profit considering a green supply chain (SC). The considered SC has three levels, including plants, distribution centers (DCs), and customers, where the manufacturer and the distributor make their decisions in an integrated structure. On the other hand, the second objective seeks to reduce the emission of environmental pollutions. Therefore, we develop a multi-period model for the Green PDP (GPDP) problem regarding perishable goods.

Perishable goods are damaged and decayed during their shelf life [3]. The freshness of a group of perishable goods, such as dairy and packaged vegetables, decreases during their shelf life, and they will be useless after a fixed lifetime [4, 5]. Customers decide to buy these goods regarding their most common visual cue, i.e., the best-before-date (BBD) [4]. The product we study in this paper, denoted by \mathcal{P} , is perishable with a specific BBD and a fixed lifetime. The more time left until the BBD, the fresher are the \mathcal{P} goods, and consequently, the more willing the customers are to buy them. Therefore, for \mathcal{P} goods, apart from the price and level of advertisement [6, 7], the freshness factor plays a vital role in the demand function [4, 8]. In addition to this, in developing the demand function, we apply three customer encouragement strategies (the return, discount, and crediting policies), which distinguishes it from the literature.

Researchers concluded that the effect of integrated P-D decisions on the profit would be much more

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remarkable for perishable goods because they are not delivered on time in the non-integrated approach [4]. Therefore, the freshness of this product reduces also during transportation [9]. Besides, some cost parameters in the PDP are uncertain in reality. To deal with the uncertainty, robust optimization is applied regarding the availability of their interval values. In summary, we develop a two-objective robust model for \mathcal{P} goods' GPDP problem ($\mathcal{P} - GPDP$). Also, the augmented Epsilon constraint (AEC) method is used to make a trade-off between the environmental and economic goals.

The major contributions of our article are summarized as follows. First, although many researchers studied the PDP problems [2, 10], as far as we deeply investigated, no research is found that develops a bi-objective multi-period optimization model with integrating P-D decisions for a specific \mathcal{P} product. In fact, in addition to maximizing the profit, the proposed model also addresses the vital goal of reducing environmental impacts. The key motivation for developing this model is to get closer to real-world conditions. Second, we develop a new demand function considering three key factors, including price, advertisement, and product freshness, as well as three encouraging strategies, including credit period, discount, and perished goods return policies. Third, we employ robust optimization to cope with the operational uncertainty of the cost parameters. After our extensive studies, robust optimization has not been used to control the uncertainty of $\mathcal{P} - GPDP$ specific problem parameters. Also, a particular case study is conducted to present the industrial application of this study.

The rest of this research is arranged as follows. Section 2 represents a summary of the PDP problem background for perishable goods. In section 3, we develop the bi-objective optimization model. Section 4 presents a robust optimization approach. In section 5, the method for creating a trade-off between the environmental and economic aims is discussed. In section 6, the performance of the expanded model is examined using a specific case study. Finally, the conclusions and future suggestions are presented.

2. LITERATURE REVIEW

We reviewed articles related to the $\mathcal{P} - GPDP$. As the literature on the PDP problem is very extensive [11], we focused more on providing PDP studies for perishable goods. Ahumada and Villalobos [12] presented a model for the operational decision-making for producing, harvesting, and distributing tomato goods. Their operational decisions included packaging, warehousing, transportation, as well as multiple harvests. To consider the effect of harvest decisions on product quality and

freshness, they estimated the color change distribution. Amorim et al. [4] presented an integrated PDP model considering a loose and fixed lifetime for perishable goods. Their goals were the minimization of the P-D costs and maximization of the delivered product's shelf life. Fahimnia et al. [13] added a PDP model to the literature considering a two-level SC. Our model is closely similar to that presented by Fahimnia et al. [13] in terms of problem dimensions. However, they did not consider the effect of perishability and many realities. Amorim et al. [14] published a survey on the PDP models that had considered perishability. They provided a new framework categorizing the models of perishability in terms of three criteria: a) Physical deterioration, b) authority boundaries, and c) customer value. Bilgen and Celebi [15] considered the PDP in a multi-site mode in a yogurt production line. Their objective function was to maximize profit where pricing was dependent on the shelf life. By presenting a review study, Diaz et al. [16] categorized PDP published papers according to criteria including production, inventory, routing, modeling method, type of objective function, and solution method. Makui et al. [17] addressed the PDP for goods with a very limited expiration date, such as calendars, using postponement policy. They employed a robust optimization to cope with the uncertainty.

Fattahi et al. [18] considered a two-level SC in which a manufacturer of perishable goods produces and distributes its products among several customers. The first aim was to reduce production, inventory, and distribution costs, while the second goal was to minimize lateral transshipment costs such that no shortage occurs for the SC. Devapriya et al. [19] developed a PDP model concerning perishability in which they paid more attention, how to distribute the product. Ensafian and Yaghoubi [20] developed an integrated model for platelet SC with two types of production methods. They took into account the PDP and presented a bi-objective robust model, maximizing the delivered platelet units' freshness while minimizing the cost. Guarnaschelli et al. [21] considered the PDP for a two-level dairy SC. They presented an integrated two-stage stochastic model. Biuki et al. [22] modeled a specific type of integrated PDP for perishable goods with inventory, location, and routing decisions by real-world data. Liu et al. [23] recently considered the integrated PDP in a blood SC containing one supplier and some blood centers while the transshipment among the blood centers was allowed.

In the perishability context, Bakker et al. [24] reviewed the developments in inventory control and distribution of perishable goods. Coelho and Laporte [25] reviewed different policies for inventory management and reprocessing of perishable goods. They analyzed three policies, including fresh-first, old-

first, and optimized priority. A few years later, Janssen et al. [26] completed Bakker et al.'s survey of perishable inventory models using key topics. Gharehyakheh et al. [27] presented an integrated model to minimize transportation costs and CO₂ emissions as well as maximize product freshness. They addressed a routing problem considering shelf life, temperature, and energy consumption prediction. Recently, Navazi et al. [28] developed a three-objective model to distribute perishable goods and gathered the remained perished goods for recycling while distributing fresh goods.

According to our in-depth studies, no article considered two-objective optimization to model GPDP for perishable goods considering the freshness factor and uncertainty. Each new contribution described in Section 1 differentiates our research from the literature.

3. MATHEMATICAL MODEL

3. 1. Problem Description This section describes our $\mathcal{P} - GPDP$ problem for an SC with three levels: plants, DCs, and customers. Consider a P-D company that has many customers in different locations. The company's first goal is to maximize its profit by integrating production, inventory, and distribution decisions for product \mathcal{P} . The product flow in the SC network is displayed in Figure 1. After identifying several potential locations for the DCs, the P-D company establishes optimal DCs with different capacities. It is not possible to relocate the DCs during the planning periods. Also, the plants and customers have pre-determined locations. Since transportation is one of the major environmental pollution sources, the P-D company's second goal is to minimize the environmental impact of transportation, regarding the vital importance of paying attention to green issues.

To reduce the risk of perishing, customers are looking to buy a product with a longer lifetime. However, the P-D company must first increase each period's production by taking into account the relevant capacity to minimize setup costs. Second, considering the transportation capacity, it must deliver more frequently and larger amounts of the product to decrease transportation costs. In developing demand function, in addition to the effect of price, product freshness, and advertisement, we apply three other strategies to attract customers and improve market share, including 1) Perished product return policy: customers can return their purchase at a specific rate, where for each unit of the returned product, a salvage value is considered, 2) Discount policy: different discounts are considered for the product with different shelf lives, 3) Credit policy:

the P-D company provides a specific credit period for the payment deadline. Therefore, under each of these policies, a special rate is considered, which is the same for different customers.

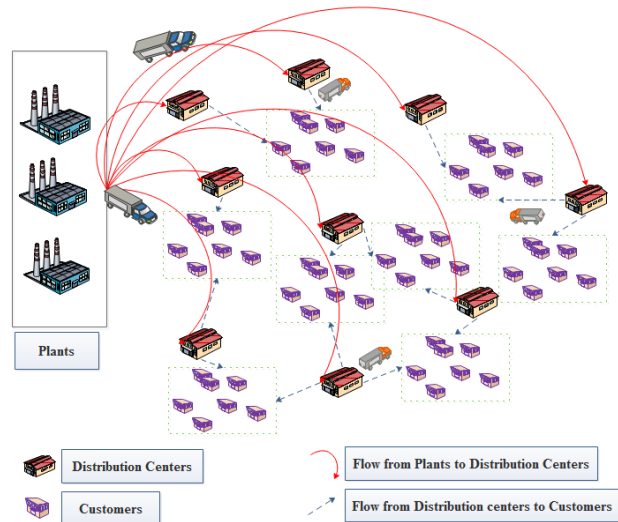


Figure 1. The three-level SC network for $\mathcal{P} - GPDP$

Moreover, the parameters of P-D costs (production and transportation) are uncertain, and in the real world, the data are available only in interval form. To deal with this operational uncertainty, we use Bertsimas and Sim's robust optimization [29]. In general, we look to reply to the following inquiries in the considered $\mathcal{P} - GPDP$ problem: 1) How to control the inventory level and plan the optimum production, such as the production periods and lot size? 2) How to determine the optimal DCs location and the optimum product flow in the network? 3) How much are the advertisement costs and customer encouragement strategies? To find an answer to these inquiries, we extend a robust optimization model to maximize the P-D profit and minimize transportation's environmental impact.

3. 2. Notations In this sub-section, the notations are defined.

Sets

- \mathcal{F} Set of plants, indexing with f
- \mathcal{D} Set of potential DCs, indexing with d
- \mathcal{K} Set of the DCs capacities, indexing with k
- \mathcal{C} Set of customers, indexing with c
- \mathcal{T} Set of periods, indexing with t
- \mathcal{H} Set of consumable periods for the product, indexing with h

Parameters

- $f c_f$ The fixed cost of setting up plant f in every period
- $q c_f$ Unit production cost in plant f (**uncertain: interval**)
- $f d c_{dk}$ Fixed establishing cost of the DC with capacity k at location d
- $t c^{f \rightarrow d}$ Transportation cost between plant f and DC d (**uncertain: interval**)
- $t c^{d \rightarrow c}$ Transportation cost between DC d and customer c (**uncertain: interval**)

hc_d^h	Holding cost of each product unit with age h during a period in DC d
cap^{f-}	Capacity of each vehicle to travel from plant f to DC d
cap^{d-}	Capacity of each vehicle to travel from DC d to customer c
$e^{f \rightarrow d}$	Environmental effects (CO ₂ production) caused by each vehicle traveling from plant f to DC d
$e^{d \rightarrow c}$	Environmental effects (CO ₂ production) caused by each vehicle traveling from DC d to customer c
cap_f	The capacity of production in plant f in every period
cap_k	The capacity of storing the product in a DC with capacity k
dem_c	Nominal demand of customer c for the fresh product
pr	Unit selling price for the fresh product
Ω	Cost of considering an entire credit for customers
Ψ	Salvage value for each unit perished product

Variables

Q_{ft}	Production amount for plant f in the period t
sz_{ft}	1, if plant f is set up in the period t ; 0, otherwise
dz_{dk}	1, if a specific DC with capacity k is established at location d ; 0, otherwise
A	Marketing cost
$f w_t^{f \rightarrow d}$	The flow of the goods from plant f to DC d for period t
$f w_{ht}^{d \rightarrow c}$	The flow of the goods with shelf life h from DC d to customer c for period t
I_{dt}^h	Product inventory with shelf life h in DC d for period t
s_1^h	The return rate of the sold product with age h
s_2^h	The discount rate of the sold product with age h
s_3^h	Credit rate of the sold product with age h
r_{ct}	The amount of product returned from customer c for period t
π^{PD}	The total profit
E^{PD}	The total amount of environmental effects (CO ₂ production resulted from transportation)

3. 3. Problem Modeling In this sub-section, we first develop the new demand function affected by price, product freshness, advertisement, and the encouragement strategies. Then, based on this demand function, we develop a bi-objective optimization model to maximize the P-D Company's profitability and minimize the environmental impacts.

3. 3. 1. Development of Demand Function

According to previous research, the potential demand depends on price as stated in Equation (1) [7, 30, 31]:

$$\mathcal{D}(pr) = \mathcal{b}(1 - \alpha \cdot pr)^{\frac{1}{v}} \tag{1}$$

where \mathcal{b} is the fresh goods' demand at the lowest price, and α and v are non-negative parameters that indicate the price elasticity of demand ($pr \leq \frac{1}{\alpha}$). Now suppose that the amount of demand $\mathcal{D}(pr)$ in Equation (1) needs

the advertisement cost \mathcal{A} . To include the impact of advertisement into the demand function, Equation (2) is obtained:

$$\mathcal{D}(pr, A) = \mathcal{D}(pr) \cdot \left(1 - \frac{\mathcal{A}-A}{\mathcal{A}}\right) = \mathcal{b}(1 - \alpha \cdot pr)^{\frac{1}{v}} \cdot \left(\frac{A}{\mathcal{A}}\right) \tag{2}$$

where $1 - \frac{\mathcal{A}-A}{\mathcal{A}}$ shows the demand reduction factor due to inadequate advertisement.

$\mathcal{D}(pr, A)$ is the demand function for fresh goods ($h = 1 \in \mathcal{H}$). Besides, if demand decreases linearly due to the lack of product freshness, the maximum market share is as Equation (3):

$$\mathcal{S}^h(pr, A) = \begin{cases} \eta \cdot \mathcal{D}(pr, A) & \forall h \in \mathcal{H} \\ 0 & \forall h > |\mathcal{H}| \end{cases} \tag{3}$$

where $\eta = 1 - \frac{h-1}{|\mathcal{H}|}$ is the freshness factor, i.e., the ratio of the remaining product shelf life.

It is evident that $\mathcal{S}^h(pr, A) < \mathcal{D}(pr, A) \forall h \in \mathcal{H} \setminus \{1\}$. In fact, due to the lack of product freshness, some potential demand ($LS = \mathcal{D}(pr, A) - \mathcal{S}^h(pr, A)$) is lost, which is compensated as much as possible by using customer encouragement strategies.

The customer encouragement strategies (the credit, return, discount policies) are applied to demand function and, accordingly, to the amount of supply. Equation (4) presents the suggested demand function as a result of these policies:

$$\mathcal{D}^h(pr, A, s_1, s_2, s_3) = \frac{\eta}{1 - (s_1 + s_2 + s_3)} \cdot \mathcal{D}(pr, A) = \frac{|\mathcal{H}| + 1 - h}{|\mathcal{H}|(1 - (s_1 + s_2 + s_3))} \cdot \mathcal{b}(1 - \alpha \cdot pr)^{\frac{1}{v}} \cdot \left(\frac{A}{\mathcal{A}}\right) \quad \forall h \in \mathcal{H} \tag{4}$$

where $\frac{\eta}{1 - (s_1 + s_2 + s_3)} = \frac{|\mathcal{H}| + 1 - h}{|\mathcal{H}|(1 - (s_1 + s_2 + s_3))}$ is the adjustment coefficient of potential demand ($\mathcal{D}(pr, A)$) regarding the four key elements of the freshness (η), return (s_1), discount (s_2) and crediting (s_3) rates ($0 \leq s_1 + s_2 + s_3 < 1$). After applying the policies, it is concluded that $\mathcal{D}^h(pr, A, s_1, s_2, s_3) \geq \eta \cdot \mathcal{D}(pr, A)$. Now if $\mathcal{S}^h(pr, A, s_1, s_2, s_3)$ is the maximum market share with applying the encouragement strategies, it will be clear that $\mathcal{S}^h(pr, A, s_1, s_2, s_3) \leq \mathcal{D}^h(pr, A, s_1, s_2, s_3)$. Thus, if $LS < \mathcal{D}^h(pr, A, s_1, s_2, s_3) - \eta \cdot \mathcal{D}(pr, A)$, not only lost sales in the current period are compensated, but it is also possible to supply some demand of the subsequent periods. In this case, regarding the encouragements, the customer will be more inclined to purchase and stock for the future.

Consequently, in every period of production and supply, the maximum demand/sale for the product with shelf life h is $\frac{|\mathcal{H}| + 1 - h}{|\mathcal{H}|(1 - (s_1 + s_2 + s_3))} \cdot \mathcal{D}(pr, A) = \frac{|\mathcal{H}| + 1 - h}{|\mathcal{H}|(1 - (s_1 + s_2 + s_3))} \cdot \mathcal{b}(1 - \alpha \cdot pr)^{\frac{1}{v}} \cdot \left(\frac{A}{\mathcal{A}}\right)$.

3. 3. 2. Proposed Formulation After defining the demand function, the objective functions are presented as follows:

$$\begin{aligned}
 \max \pi^{PD} = & \\
 pr \cdot \sum_{d \in \mathcal{D}} \sum_{c \in \mathcal{C}} \sum_{h \in \mathcal{H}} \sum_{t \in \mathcal{T}} fw_{ht}^{d \rightarrow c} - & \\
 \left(\left[\sum_{f \in \mathcal{F}} \sum_{t \in \mathcal{T}} fc_f \cdot sz_{ft} \right] + \right. & \\
 \left[\sum_{f \in \mathcal{F}} \sum_{t \in \mathcal{T}} qc_f \cdot Q_{ft} \right] + & \\
 \left[\sum_{d \in \mathcal{D}} \sum_{k \in \mathcal{K}} fd_{dk} \cdot dz_{dk} \right] + & \\
 \left[\sum_{d \in \mathcal{D}} \sum_{h \in \mathcal{H}} \sum_{t \in \mathcal{T}} hc_{dt}^h \cdot I_{dt}^h \right] + & \\
 \left[\sum_{f \in \mathcal{F}} \sum_{d \in \mathcal{D}} \sum_{t \in \mathcal{T}} tc^{f \rightarrow d} \left[\frac{fw_t^{f \rightarrow d}}{cap^{f \rightarrow d}} \right] + \right. & \quad (5) \\
 \left. \sum_{d \in \mathcal{D}} \sum_{c \in \mathcal{C}} \sum_{h \in \mathcal{H}} \sum_{t \in \mathcal{T}} tc^{d \rightarrow c} \left[\frac{fw_{ht}^{d \rightarrow c}}{cap^{d \rightarrow c}} \right] \right] + & \\
 \left[\sum_{d \in \mathcal{D}} \sum_{c \in \mathcal{C}} \sum_{h \in \mathcal{H}} \sum_{t \in \mathcal{T}} (s_2^h \cdot pr + \right. & \\
 \left. \Omega \cdot s_3^h) fw_{ht}^{d \rightarrow c} \right] + \left[\sum_{c \in \mathcal{C}} \sum_{t \in \mathcal{T}} (pr - \Psi) r_{ct} \right] + & \\
 [A] &
 \end{aligned}$$

$$\begin{aligned}
 \min E^{PD} = & \\
 \left[\sum_{f \in \mathcal{F}} \sum_{d \in \mathcal{D}} \sum_{t \in \mathcal{T}} e^{f \rightarrow d} \left[\frac{fw_t^{f \rightarrow d}}{cap^{f \rightarrow d}} \right] + \right. & \quad (6) \\
 \left. \sum_{d \in \mathcal{D}} \sum_{c \in \mathcal{C}} \sum_{h \in \mathcal{H}} \sum_{t \in \mathcal{T}} e^{d \rightarrow c} \left[\frac{fw_{ht}^{d \rightarrow c}}{cap^{d \rightarrow c}} \right] \right] &
 \end{aligned}$$

Equation (5) shows the objective function of profit maximization for the P-D company. Its first section is the income from the sale of the product. The second section shows the total costs, including nine subsections. The first one is the setup cost for the plants. The second one addresses the variable cost of production. The third one shows the fixed cost for establishing the DCs. In the fourth subsection, the inventory cost is calculated. Subsections 5 and 6 are the costs of transporting the product. $\left[\frac{fw_t^{f \rightarrow d}}{cap^{f \rightarrow d}} \right]$ and $\left[\frac{fw_{ht}^{d \rightarrow c}}{cap^{d \rightarrow c}} \right]$ are the number of vehicles for transporting from a specific plant to the DCs and then to the customers. The expressions $\left[\frac{fw_t^{f \rightarrow d}}{cap^{f \rightarrow d}} \right]$ and $\left[\frac{fw_{ht}^{d \rightarrow c}}{cap^{d \rightarrow c}} \right]$ are linearized according to Equations (7) and (8).

$$\begin{cases} n_t^{f \rightarrow d} \geq \frac{fw_t^{f \rightarrow d}}{cap^{f \rightarrow d}} \\ n_t^{f \rightarrow d} < \frac{fw_t^{f \rightarrow d}}{cap^{f \rightarrow d}} + 1 \\ n^{f \rightarrow d} \in \mathbb{Z}^+ \end{cases} \quad (7)$$

$$\begin{cases} n_t^{d \rightarrow c} \geq \sum_{h \in \mathcal{H}} \frac{fw_{ht}^{d \rightarrow c}}{cap^{d \rightarrow c}} \\ n_t^{d \rightarrow c} < \sum_{h \in \mathcal{H}} \frac{fw_{ht}^{d \rightarrow c}}{cap^{d \rightarrow c}} + 1 \\ n_t^{d \rightarrow c} \in \mathbb{Z}^+ \end{cases} \quad (8)$$

Subsection 7 is the costs of applying discount and credit policies to customers. In the eighth subsection, the cost resulted from the product return policy is subtracted, and the salvage value of the perished goods is added to the profit. Finally, the ninth subsection shows the cost of advertisement. Equation (6) shows the second

objective function, minimizing the environmental effects of transportation. In the following, the constraints of the developed model are given:

$$\sum_{d \in \mathcal{D}} fw_{ht}^{d \rightarrow c} = \frac{|\mathcal{A}|+1-h}{|\mathcal{A}|(1-(s_1^h+s_2^h+s_3^h))} \cdot dem_c (1 - \quad (9)$$

$$\alpha \cdot pr)^{\frac{1}{v}} \cdot \left(\frac{A}{\mathcal{A}} \right) \quad \forall c \in \mathcal{C}, h \in \mathcal{H}, t \in \mathcal{T}$$

$$Q_{ft} \leq cap_f \cdot sz_{ft} \quad \forall f \in \mathcal{F}, t \in \mathcal{T} \quad (10)$$

$$Q_{ft} = \sum_{d \in \mathcal{D}} fw_t^{f \rightarrow d} \quad \forall f \in \mathcal{F}, t \in \mathcal{T} \quad (11)$$

$$I_{dt}^h = \sum_{f \in \mathcal{F}} fw_t^{f \rightarrow d} - \sum_{c \in \mathcal{C}} fw_{ht}^{d \rightarrow c} \quad \forall d \in \mathcal{D}, t \in \mathcal{T}, h = 1 \quad (12)$$

$$I_{dt}^h = I_{dt-1}^{h-1} - \sum_{c \in \mathcal{C}} fw_{ht}^{d \rightarrow c} \quad \forall d \in \mathcal{D}, t \in \mathcal{T}, h \in \mathcal{A} \setminus \{1\} \quad (13)$$

$$\sum_{f \in \mathcal{F}} fw_t^{f \rightarrow d} \leq \sum_{k \in \mathcal{K}} cap_k \cdot dz_{dk} \quad \forall d \in \mathcal{D}, t \in \mathcal{T} \quad (14)$$

$$\sum_{h \in \mathcal{H}} I_{dt}^h \leq \sum_{k \in \mathcal{K}} cap_k \cdot dz_{dk} \quad \forall d \in \mathcal{D}, t \in \mathcal{T} \quad (15)$$

$$\begin{cases} A, Q_{ft}, fw_t^{f \rightarrow d}, fw_{ht}^{d \rightarrow c}, I_{dt}^h, s_1^h, s_2^h, s_3^h, r_{ct} \geq 0 \\ sz_{ft}, dz_{dk} \in \{0,1\} \end{cases} \quad (16)$$

Equation (9), is based on the developed demand function, shows the maximum demand/sale of goods with shelf life h in each period. In Equation (10), subject to the plant setup, the maximum production in each plant is restricted to its capacity. Equation (11) is an equilibrium constraint for each plant's production amount and the supply amount to the DCs. According to Equation (12), the inventory for a quite fresh product (h = 1) in every DC is equal to the amount taken from the plants minus the supply to the customers. Equation (13) relates to the inventory of non-fresh goods. In Equation (14), subject to a DC's establishment, the transportation amount from the plants to the DC is limited to its capacity. Equation (15) refers to the bounded capacity of the Dcs to store goods with different shelf life. Finally, Equation (16) describes the range of the decision variables.

4. UNCERTAINTY CONTROL

In our problem, the parameters of production and transportation costs have constraint-wise uncertainty and are considered as an interval. Some other parameters may also be uncertain. However, we assume that some of them, such as the demand, are in the worst-case situation. Besides, the uncertainty of the other parameters, such as capacity, is not to the extent to be considered; thus, we assume their uncertainty is negligible. In this paper, Bertsimas and Sim (B&S) method [29] is used to achieve solution robustness. The

B&S method is employed because it works right for the constraint-wise uncertainty, and it can control the conservatism level. Some researchers used this method to deal with this kind of operational uncertainty, as well [32]. To explain the B&S method, first consider the following optimization model in general:

$$\min_x \sum_{j \in J} a_{0j} x_j \text{ s.t. } Ax \leq b \tag{17}$$

where a_{0j} are uncertain parameters. Based on robust programming (RP), the above optimization problem is solved under uncertainty in such a way that the solution will always be feasible, and the amount of the objective function is optimal in the strict case [33]–[35]. Therefore, if the uncertain parameters are assumed to be as $a_{0j} \in [a_{0j}^L, a_{0j}^U]$, then the robust counterpart (RC) of the above uncertain model is as follows:

$$\min_x \max_{a_{0j} \in [a_{0j}^L, a_{0j}^U]} \{ \sum_{j \in J} a_{0j} x_j \} \text{ s.t. } Ax \leq b \tag{18}$$

If we consider the nominal value of the parameter as $\bar{a}_{0j} = \frac{a_{0j}^L + a_{0j}^U}{2}$ and the deviation of each parameter from the nominal value as $\widehat{a}_{0j} = a_{0j}^U - \bar{a}_{0j}$, in an RP approach proposed by B&S [29], the conservatism level is controlled by defining a parameter $0 \leq \Gamma \leq |J|$ and presenting a new RC. Then, the RC of the above objective function is as follows:

$$\begin{aligned} & \min_{x: Ax \leq b} t \\ & \text{s.t.} \\ & \sum_{j \in J} \bar{a}_{0j} x_j + \\ & \max_{\{S \cup \{t\} | S \subseteq J, |S| = |\Gamma|, t \in S \cup J\}} \left\{ \sum_{j \in S} \widehat{a}_{0j} |x_j| + \right. \\ & \left. (\Gamma - |J|) \widehat{a}_{0t} |x_t| \right\} \leq t \end{aligned} \tag{19}$$

In the B&S article, based on the strong duality theorem, it is proved that the above model is equivalent to the following linear model. It should be explained that the considered problem meets the condition of having non-negative decision variables.

$$\begin{aligned} & \min_{x: Ax \leq b} t \\ & \text{s.t.} \\ & \sum_{j \in J} \bar{a}_{0j} x_j + \Gamma \cdot q_0 + \sum_{j \in J} p_{0j} \leq t \\ & q_0 + p_{0j} \geq \widehat{a}_{0j} x_j \quad \forall j \in J \\ & q_0, p_{i0} \geq 0 \quad \forall j \in J \end{aligned} \tag{20}$$

In the above robust model, known as the B&S method, if $\Gamma = 0$, only the nominal values of the parameters are considered. In this case, the conservatism is very insignificant due to ignoring the parameters perturbation. The more $\Gamma \rightarrow |J|$, the more conservative the model.

Regarding the uncertainty of the unit production cost in plant f (qc_f), transportation cost between plant f and DC d ($tc^{f \rightarrow d}$), and transportation cost between DC d and customer c ($tc^{d \rightarrow c}$), uncertain quantities are

replaced with the production and transportation costs in the objective function. Also, Equation (21) is added to the optimization problem.

$$\begin{aligned} \theta \geq & \sum_{f \in \mathcal{F}} \sum_{t \in \mathcal{T}} qc_f \cdot Q_{ft} + \\ & \sum_{f \in \mathcal{F}} \sum_{d \in \mathcal{D}} \sum_{t \in \mathcal{T}} tc^{f \rightarrow d} n_t^{f \rightarrow d} + \\ & \sum_{d \in \mathcal{D}} \sum_{c \in \mathcal{C}} \sum_{t \in \mathcal{T}} tc^{d \rightarrow c} n_t^{d \rightarrow c} \end{aligned} \tag{21}$$

Finally, regarding the general form (20), the robust counterpart of the above equations replaces.

5. TRADE-OFF OBJECTIVE FUNCTIONS

To solve two/multi-objective optimization problems (MODM), various approaches were proposed, including the weighted sum method (WSM), Epsilon constraint (EC), augmented Epsilon constraint (AEC), goal programming (GP), and lexicographic (Lex). The general MODM problem is formulated as model (22).

$$\begin{cases} \text{Min } (f_1(x), f_2(x), \dots, f_n(x)) \\ x \in X \end{cases} \tag{22}$$

Suppose the first goal is the main goal, and the other objectives are restricted to a higher bound and are applied as the constraints of the problem. If the EC method is used, the following single-objective model is obtained:

$$\begin{cases} \text{Min } f_1(x) \\ f_i(x) \leq \varepsilon_i \quad i = 2, 3, \dots, n \\ x \in X \end{cases} \tag{23}$$

where the second to n th targets are limited to the maximum value of ε_i . In model (23), different solutions are achieved by changing the values of ε_i , which may fail to be efficient. By partially amending model (23), known as the AEC method, the mentioned demerit can be solved. To better implement the AEC method, the appropriate initial range of ε_i can be obtained from Lex [36]. In the AEC method, first, a suitable range of ε_i changes must be determined. Then, for different values of ε_i , the Pareto front must be obtained. The AEC model is as follows:

$$\begin{cases} \text{Min } f_1(x) - \sum_{i=2}^n \phi_i s_i \\ f_i(x) + s_i = \varepsilon_i \quad i = 2, 3, \dots, n \\ x \in X \\ s_i \geq 0 \end{cases} \tag{24}$$

where s_i is a non-negative variable for slack, and ϕ_i is a parameter for normalizing the first objective function value relative to objective i ($\phi_i = \frac{R(f_1)}{R(f_i)}$). In the proposed AEC method, we first set the range $\varepsilon_i \in [\text{Min}(f_i), \text{Max}(f_i)]$ based on the Lex method for the objectives, and after setting ε_i , we solve the proposed robust model. Therefore, the final robust and single-objective model is as follows:

$$\begin{aligned} \max \pi^{PD} = & pr \cdot \sum_{d \in \mathcal{D}} \sum_{c \in \mathcal{C}} \sum_{h \in \mathcal{H}} \sum_{t \in \mathcal{T}} f w_{ht}^{d \rightarrow c} - \\ & \left(\begin{aligned} & [\sum_{f \in \mathcal{F}} \sum_{t \in \mathcal{T}} f c_f \cdot s z_{ft}] + \\ & [\sum_{d \in \mathcal{D}} \sum_{k \in \mathcal{K}} f d c_{dk} \cdot d z_{dk}] + \\ & [\sum_{d \in \mathcal{D}} \sum_{h \in \mathcal{H}} \sum_{t \in \mathcal{T}} h c_d^h \cdot l_{dt}^h] + \\ & [\sum_{d \in \mathcal{D}} \sum_{c \in \mathcal{C}} \sum_{h \in \mathcal{H}} \sum_{t \in \mathcal{T}} (s_2^h \cdot pr + \Omega \cdot s_3^h) f w_{ht}^{d \rightarrow c}] + \\ & [\sum_{c \in \mathcal{C}} \sum_{t \in \mathcal{T}} (pr - \Psi) r_{ct}] + [A] + \theta + \phi \cdot w \end{aligned} \right) \end{aligned} \quad (25)$$

$$\begin{aligned} & \left[\sum_{f \in \mathcal{F}} \sum_{d \in \mathcal{D}} \sum_{t \in \mathcal{T}} e^{f \rightarrow d} \left[\frac{f w_t^{f \rightarrow d}}{cap^{f \rightarrow d}} \right] + \right] + \\ & \left[\sum_{d \in \mathcal{D}} \sum_{c \in \mathcal{C}} \sum_{h \in \mathcal{H}} \sum_{t \in \mathcal{T}} e^{d \rightarrow c} \left[\frac{f w_{ht}^{d \rightarrow c}}{cap^{d \rightarrow c}} \right] \right] + \\ & w = \varepsilon \text{ (Corresponding to } E^{PD}) \\ & RC \left(\begin{aligned} & \theta \geq \sum_{f \in \mathcal{F}} \sum_{t \in \mathcal{T}} q c_f \cdot Q_{ft} + \\ & \left(\sum_{f \in \mathcal{F}} \sum_{d \in \mathcal{D}} \sum_{t \in \mathcal{T}} t c^{f \rightarrow d} n_t^{f \rightarrow d} + \right. \\ & \left. \sum_{d \in \mathcal{D}} \sum_{c \in \mathcal{C}} \sum_{t \in \mathcal{T}} t c^{d \rightarrow c} n_t^{d \rightarrow c} \right) \\ & x \in X \\ & w \geq 0 \end{aligned} \right) \end{aligned} \quad (26)$$

where $x \in X$ represents all the constraints of the developed model in the previous sections. In the next section, model (25) is run for a case study to evaluate and analyze the developed model’s output.

6. NUMERICAL RESULTS

In this section, a case study is carried out to prove the extended model’s applicability. It should be noted that we used GAMS software to implement the model.

6. 1. Case Study Saida Company in Isfahan is a manufacturer and distributor of ready-to-eat foodstuffs as perishable goods. The company’s plants are located on Isfahan’s outskirts, and the company does not have DCs inside the city. Therefore, to distribute its perishable goods inside the city, it requires establishing DCs in appropriate locations and pursuing its PDP in an integrated manner. By investigating the sales amount and longevity of the goods, we concluded that optimizing the P-D decisions of one certain product, lettuce, is more important at present. In the following, we name Saida Company as S company. The price and freshness of lettuce have a notable effect on sales. S company applies the three proposed strategies to increase its market share.

S company has established two plants ($\mathcal{F} = \{1,2\}$) located outside the city of Isfahan. After meetings with the managers, it was concluded that the number of candidate locations for the DCs is 12 locations ($\mathcal{D} = \{1,2, \dots, 12\}$) with three types of capacity ($\mathcal{K} = \{1,2,3\}$). The capacity of these DCs is 1500, 750, and 500, respectively. According to the clustering, customers are centralized in 20 points of the city ($\mathcal{C} = \{1,2, \dots, 20\}$). The product has a shelf life of 4 days ($\mathcal{H} = \{1,2, \dots, 4\}$)

and the P-D decisions are made in a 30-day cycle ($\mathcal{T} = \{1,2, \dots, 30\}$). S company gives each unit of the product at a price of 120,000 Rials to the market. To facilitate calculations, we consider each unit’s price equal to 12,000 Tomans and express every thousand Tomans as a unit in all the income and costs.

6. 2. Result Analysis

6. 2. 1. Determining the Pareto Front and the Best Solution

After running the developed robust model, the Pareto optimal solutions are obtained regarding the model’s objectives and the used trade-off. Given the uncertainty of some cost parameters and the robust approach, we assume that $\Gamma = 6800$. We should note that the sensitivity analysis on the amount and how to adjust this parameter is presented in the following subsections.

Table 1 shows the corresponding payoff matrix. The Pareto front is also obtained, as shown in Figure 2. According to Figure 2, as the second objective, i.e., the minimization of the environmental impacts, gets worse, the first objective, i.e., the profit, improves. In other words, to the extent that an increase in greenhouse gas emissions is allowed (the second goal gets worse), there is much more profit. But from a specific value onwards, although the second objective worsens, not much profit is made for the first objective. Therefore, that point would be a practical solution for reporting to the management. Consequently, we select the Pareto solution of 110,000 and 9,050 units, respectively, for the first and second objectives and present the subsequent analysis based on this solution.

TABLE 1. The payoff matrix

	π^{PD}	E^{PD}
π^{PD}	112,300	67,000
E^{PD}	10,000	8,150

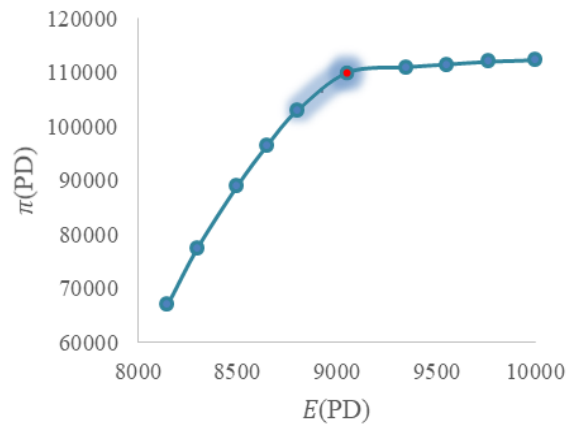


Figure 2. The Pareto front

In the following, some of the most important outputs of the robust model are reported based on Pareto’s best-selected solution. The optimal amount of advertisement costs is 43,940 units. The optimal amount of production in the first seven periods is given in Table 2. Table 3 reports the optimal rates. Because only the perished goods are accepted for return, the return rate on the fourth day of a product age is obtained ten percent ($s_1^4 = 0.1$).

After receiving the location result, it is determined that four DCs out of 12 potential locations will be established in the optimal solution. The location of the activated DCs is shown in Figure 3. One large-capacity DC, two medium-capacity DCs, and one small-capacity DC should be established. Additionally, the S company’s profit in the best-selected solution is 110,000 units, 30,000 units more than when it does not use our integrated GPDP model.

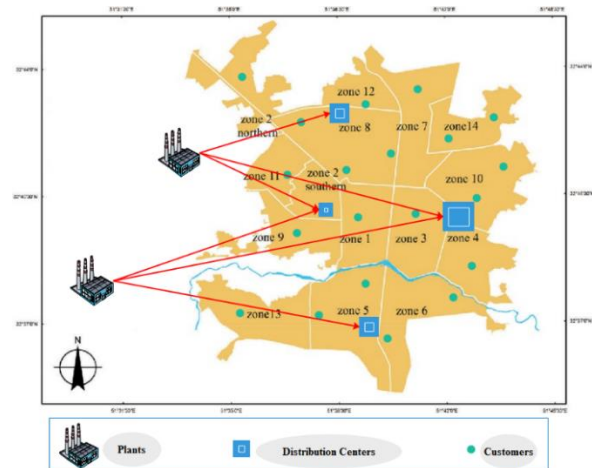


Figure 3. The established DCs

6. 2. 2. Robustness and Conservatism Analysis

We analyzed model robustness and how to adjust the conservatism coefficient (Γ). For this purpose, the conservatism coefficient value has changed from the maximum to minimum, and it is assumed that the value of the first objective, i.e., the profit, is considered. According to the uncertain parameters and their dimensions, the maximum value for Γ is 7,980, indicating that the uncertainty of the parameters is completely controlled. When one hundred percent conservatism is applied, the profit will be at its lowest value. As the conservatism decreases, the profit definitely increases. Figure 4 shows the changes in the profit over the percentage changes in conservatism. The percentage of conservatism is actually the percentage of uncertainty that is controlled. This figure illustrates well the effect of conservatism on the profit. In fact, by reducing the conservatism from the specified amount onwards, there is no significant profit increase. Therefore, that point is a proper solution to the conservatism coefficient we considered in the previous subsections.

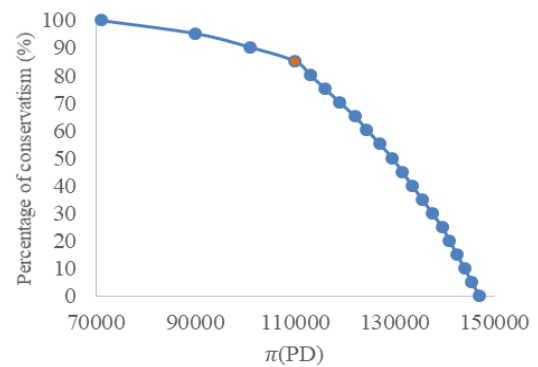


Figure 4. The profit changes affected by the conservatism

TABLE 2. The optimal amount of production in the first week

f	t	1	2	3	4	5	6	7
1		2000	1500	0	1000	2000	1500	0
2		1500	1000	0	0	1500	0	0

TABLE 3. The optimal discount and credit rates

h	s_2^h	s_3^h
1	0	0
2	0.1	0.05
3	0.2	0.1
4	0.45	0.25

6. 3. Sensitivity Analysis

6. 3. 1. The Encouragement Strategies and P-D Parameters

We analyzed the effect of unit production, transportation, setup costs and the impact of applying the encouragement strategies on the profit. In Figure 5, the profit decreases due to the rise in the unit production cost. Figure 6 shows an almost linear decline in the profit as the transportation costs increased. Finally, Figure 7 shows the trend of declining profit in exchange for an increase in fixed setup costs, which has less effect on the profit than does the unit production cost. Besides, in Figure 8, it is seen that the profit increases by considering each of the proposed strategies. The maximum profit is obtained when all three encouragement strategies were applied.

6. 3. 2. The Demand Function

In addition to previous sensitivity analysis, we investigate here the impact of some parameters from the developed demand function, i.e., α , v , and β , on the potential demand and supply, income, and the encouragement strategies.

Figures 9, 10, and 11 analyze the change in the coefficients α and v and parameter β .

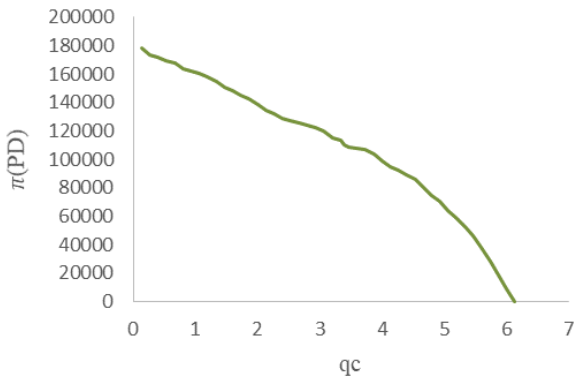


Figure 5. The impact of the unit production cost changes

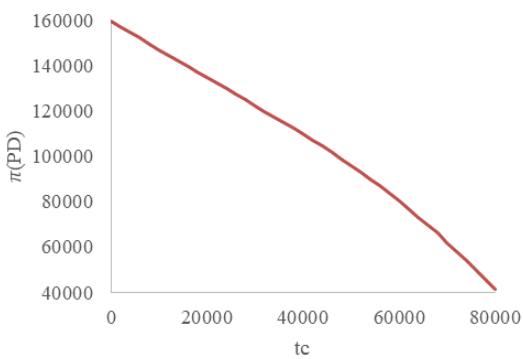


Figure 6. The impact of the transportation cost changes

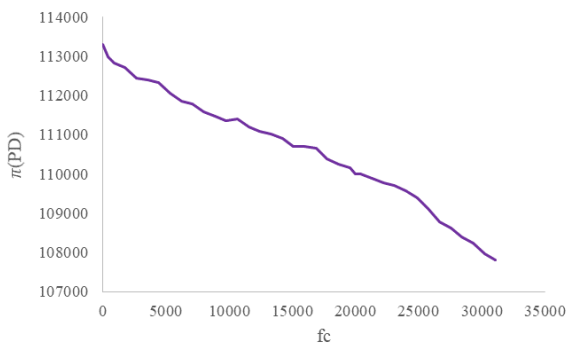


Figure 7. The impact of the setup cost changes

Considering Figure 9a, the potential demand and the supply decrease by an increase in α . From $\alpha = 0.14$ onwards, step by step, S company meets the potential demand. Figure 9b depicts an increase in the potential demand and the supply as v increases. The growing trend for the supply continues to the point that S company fails to supply more due to its limited capacity. Indeed, from roughly $v = 1$, S company cannot follow the potential demand. From Figure 9c, it is seen that the potential demand has an increasing linear trend by an increase in ℓ and the supply goes up,

as well. It can be understood that S company fails to meet the potential demand from $\ell = 168,000$ onwards.



Figure 8. The impact of the proposed strategies on the profit

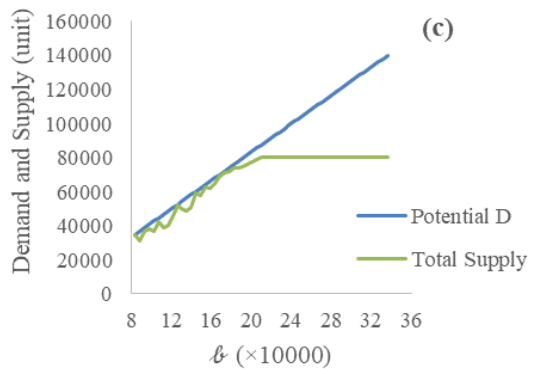
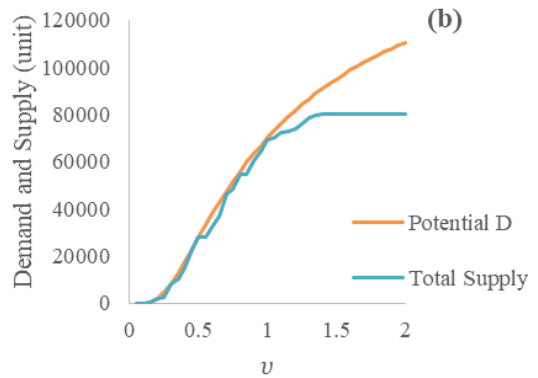
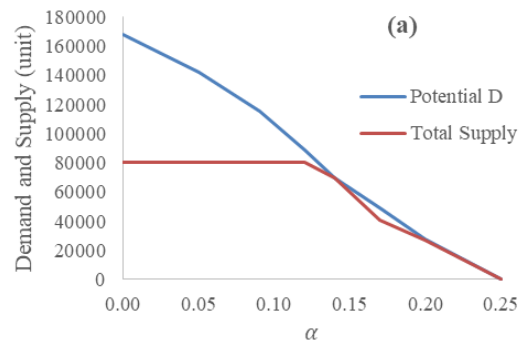


Figure 9. The analysis of α , v , and ℓ on the demand/supply

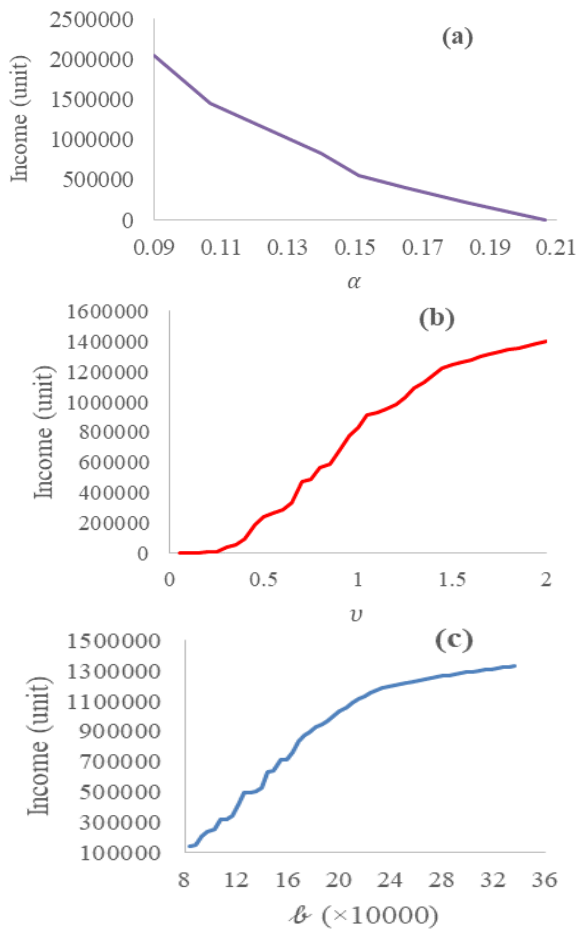


Figure 10. The analysis of α , v , and b on the income

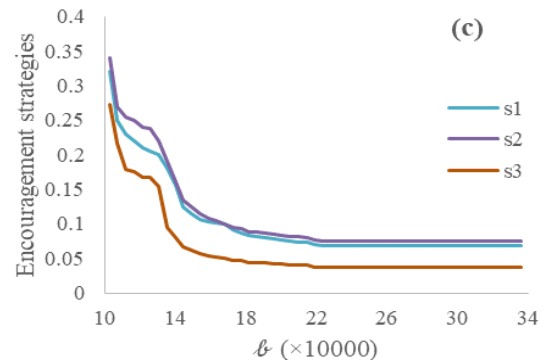
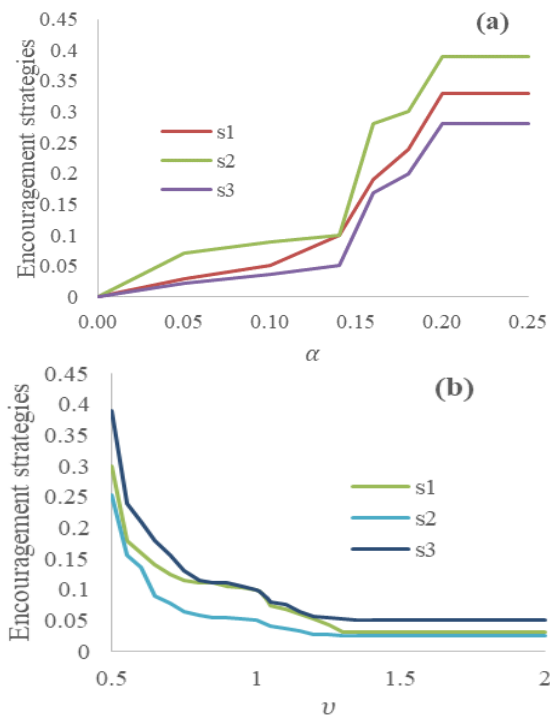


Figure 11. The analysis of α , v , and b on the strategies

Figure 10a shows the downtrend of the income for an increase in α . Figures 10b and 10c show the increasing trend of the income by an increase in v and the parameter b , respectively. Figure 11a indicates that the encouragement strategies have a rising trend by an increase in α . Indeed, the encouragement strategies must compensate for the decreased potential demand observed in Figure 9a. As demonstrated in Figure 11b, the amount of encouragement strategies goes down when coefficient v is increased. As the potential demand has an increasing manner with the rise in v , the encouragement strategies are not required to be increased. For the same reason, in Figure 11c, the encouragement strategies show a reducing trend in exchange for the rise in parameter b .

7. CONCLUSIONS

In this work, we focused on a bi-objective P-D optimization problem for perishable goods under uncertainty. The first goal was to maximize the P-D company's profit in an SC with three levels: plants, DCs, and customers. After considering the economic dimension, regarding the importance of green issues in distribution problems, the second goal was to minimize the environmental impact. In fact, for the P-D company, which owns its plants and DCs, we pursued the optimum solution for its location, inventory, production, and distribution problems. To make a trade-off between the environmental and economic goals and obtain the Pareto front, we used the augmented Epsilon constraint method. Then, we conducted a real case study to verify the application of our developed model. Concerning the control of uncertainty through Bertsimas and Sim's approach, we analyzed model robustness and how properly the conservatism coefficient was adjusted. We also performed other sensitivity analyses on the problem's main parameters to achieve some significant management results. Finally, the numerical results using the case study data showed the developed model's efficiency and performance. With the aim of industrial

application, this research brings optimization models close to real-world conditions, especially by considering the operational uncertainty. Some managerial insights can be obtained from this research as follows:

- Considering the product freshness in developing the demand function and modeling the PDP in an integrated structure can prevent the goods' perishability to an acceptable extent.
- Employing the perished product return, discount, and crediting strategies can significantly compensate for the lost market share.
- Considering the P-D decisions in an integrated framework can increase the profit, in addition to a decrease in the environmental effects.
- Coping with the operational uncertainty using the B&S robust optimization creates rational and realistic conservatism, model robustness and prevents risk in the decision-making.
- Using the developed two-objective model, we obtained solutions with a significant reduction in environmental effects at the cost of a slight reduction in the final profit.

In summary, the key contributions are as follows. First, we developed a two-objective multi-period optimization model that for the first time addresses the integrated P-D decisions for specific \mathcal{P} goods. The objectives were to maximize the profit and minimize the emission of environmental pollution. Second, a new demand function was introduced considering three key factors, including price, advertisement, and product freshness, as well as three customer encouraging strategies, i.e., the discount, return, and credit policies. Third, we utilized robust optimization to cope with the operational uncertainty of the production and transportation costs. There are some suggestions to develop this paper. For instance, one can model the freshness factor impact on demand function in a nonlinear approach. Other methods for controlling the uncertainty, such as stochastic programming, can be used. It will also be valuable to provide meta-heuristic approaches to solve large-scale problems. Finally, more SC levels can be considered, and the model can be extended for multi-product situations.

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Persian Abstract

چکیده

این مقاله، یک مدل بهینه‌سازی دوهدفه را برای برنامه‌ریزی یکپارچه تولید-توزیع چنددوره‌ای محصولات فسادپذیر تحت شرایط عدم قطعیت، توسعه می‌دهد. هدف اول، سود را در یک زنجیره تأمین سه سطحی شامل کارخانه‌ها، مراکز توزیع و مشتریان، حداکثر می‌نماید. از آنجایی که موضوع حمل‌ونقل در مسئله توزیع، یکی از مهم‌ترین منابع آلودگی‌های زیست‌محیطی است؛ هدف دوم در پی کمیته‌سازی انتشار آن‌هاست. در مسئله موردنظر، تصمیمات تولید، مکان‌یابی، موجودی و توزیع به‌صورت یکپارچه، اتخاذ می‌شوند. علاوه بر قیمت، با توجه به فسادپذیر بودن محصول، اثر تازگی محصول نیز در توسعه تابع تقاضا، اعمال می‌گردد. همچنین، جهت تشویق مشتریان، سه استراتژی شامل سیاست‌های بازگشت محصول فاسد، تخفیف، و دوره اعتباری، پیشنهاد می‌شوند. به‌منظور مقابله با عدم قطعیت درونی برخی پارامترهای هزینه، بهینه‌سازی استوار اعمال می‌شود. به‌منظور نشان دادن کاربردپذیری مدل توسعه‌یافته و نیز عملی بودن لحاظ جنبه زیست‌محیطی، یک مطالعه موردی، انجام می‌شود. محاسبات عددی روی مطالعه موردی، موازنه‌ای را بین اهداف زیست‌محیطی و اقتصادی، ارائه می‌کند و ۳۷.۵ درصد افزایش سود را با استفاده از مدل توسعه داده‌شده، نشان می‌دهد.
