RESEARCH ARTICLE

A hybrid optimization method to design a sustainable resilient supply chain in a perishable food industry

Mahyar Abbasian[1] · Zeinab Sazvar[1] · Mohammadhossein Mohammadisiahroudi[2]

Abstract

To integrate the location, inventory, and routing (LIR) problems arising in designing a resilient sustainable perishable food supply network (RSPFSN), a bi-objective optimization model is developed. To improve the resiliency and sustainability of the RSPFSN, a dynamic pricing strategy is used to cope with the disrupting events, along with minimizing the total cost and CO_2 emission of the whole network. One of the important features of the proposed model is taking into account the effects of route disruptions and traffic conditions on the deterioration of products. To solve the mixed-integer nonlinear bi-objective optimization model, a novel hybrid method is developed using the Heuristic Multi-Choice Goal Programming and Utility Function Genetics Algorithm (HMCGP-UFGA). To improve resiliency, the dynamic pricing strategy, considering the traffic condition, can lead to around a 20% improvement in both cost and CO_2 emission, based on the results of our case study in a dairy supply chain. Besides, the results of sensitivity analysis display the high flexibility of the proposed approach for various problems.

Keywords Food supply chain · Location-inventory-routing (LIR) · Sustainability · Resiliency · Perishable products · Responsible Editor: Philippe Garrigues

Introduction

The food supply chain differs from other chains in various industries in several ways, one of which is the considerable and continual diminishing in the quality of food products through the supply network (Bloemhof and Soysal 2017). Usually, the freshness of products is not constant and decreases over time until the expiration of the product (Babazadeh and Sabbaghnia 2018). In 2019–2020, the pandemic, caused by COVID-19, bolded the importance and susceptibility of the food supply chain against disruptive events (Aday and Aday 2020). For instance, dairy farmers in American cooperatives considered that 14 million liters of milk is being dumped every day due to interrupted supply chains. In England, the chair of dairy farmers reported that approximately five million liters of milk is at risk in a week. Furthermore, it was reported that tea plants are being lost because of the logistical challenges in India (BBC 2020).

Designing a perishable food supply network should therefore be considered regarding its special features that involve a variety of decisions such as locating facilities, finding best routes, and balancing the rate of producing, storing, and selling products. Because of the perishability of food products and the operations needed for manufacturing, processing, and distributing them, addressing sustainable development, i.e., economic, social, and environmental issues, in food supply chains is unavoidable. Customers, public, and private decision-makers are increasingly interested in designing sustainable supply chains (Gholizadeh et al. 2020a; Sazvar and Sepehri 2020; Bhattacharya et al. 2021; De et al. 2021). Nowadays, customers not only care about how food is processed, manufactured, and distributed but also contribute to decreasing the impacts of the food industry on the

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environment and the health of society (Navazi et al. 2021). On the other hand, governors and policymakers have put pressure on the food manufacturers and distributors to monitor their social and environmental impacts (Nicholson et al. 2011).

Another characteristic of food supply chains is the importance of logistic decisions since the distribution of perishable food has a pivotal role in the survival of food companies in a competitive market. Therefore, it is indispensable and important to manage perishable food transportation through the network, besides route management and optimal investments in marketing. Viewed in this way, limited time windows, high transportation frequency, and traffic congestion increase the costs of the system. As well, since the perishable cargo transportation system highly increases pollution in the atmosphere (Zulvia et al. 2020), various factors affecting gas emissions, such as the type of vehicles, slope of roads, and traffic conditions, should not be ignored. Therefore, the redundancy of transporting perishable goods and supplying products to promote sustainable development is undeniable.

One major approach to integrating the logistical decisions is the location-inventory-routing (LIR) problem which is well-noticed in designing supply networks to reduce costs and increase competitiveness. Which route and by which place the product is selected to be transported to the destination and how much of the product is stored are crucial to reduce costs (Ahmadi-Javid and Seddighi 2012). This problem is of special importance in the supply chains of perishable goods because of the costs of product holding, quality loss, and product spoilage in addition to the cost of losing sales due to a lack of timely supply (Li and Teng 2018). Therefore, the location of the facilities, the distance between them, and the transportation system become more important for perishable products. Improper selection for distribution centers causes problems in the routing of vehicles and transportation as well as the unbalanced workload of distribution centers. Given that, inventory costs are directly related to the location of the facility, and improper choice of facility location increases inventory costs. Delivery time, which is the most important factor in the distribution process due to the short life of food, is also affected by the decision about facility location. Moreover, the ordering time depends on various factors such as shipping mode. Different modes of transportation involve an inverse relationship between cost and time. Considering decisions on location, allocation, routing, and inventory management separately leads to suboptimization, while integrating these decisions into designing a food supply chain can greatly contribute to reducing costs, increasing responsiveness, and improving customer service levels (Yavari et al. 2020). More specifically, with increasing efficiency in transportation systems, routing and inventory decisions are influential. Hence, an integrated LIR decision for perishable food products is an inevitable

necessity. However, previous studies on LIR problems (for example, Zheng et al. 2019; Asadi et al. 2018; Karakostas et al. 2019) have rarely studied this issue.

The LIR problem will be more difficult if we also consider the fact that supply chains are due to some disruptions such as natural disasters, strikes, sanctions, and terrorist attacks leading to short-term or long-term loss of sales, delays in orders, increased shipping costs, increased consumption of energy, and environmental impacts (Rayat et al. 2017). To do this, the researchers used flexibility strategies to reduce the supply chain's risk effects, such as additional inventory holding, twice allocation, using backup facilities, allowing backup capacity reservation, multi-resource provisioning, and facility enrichment (see, for example, Fahimnia and Jabbarzadeh 2016; Rezapour et al. 2017; Zahiri et al. 2017; Jabbarzadeh, et al. 2016a; Yavari and Zaker 2020).

The main goal of this research is examining the mentioned key aspects related to perishable food supply chains, such as environmental impact, economical aspect, and resiliency, along with focusing on essential innovative factors in theory and practice, including traffic condition and its effect on perishability. Accordingly, this study presents a mixed-integer multi-objective optimization model minimizing the costs and environmental impacts of a food supply network inspired from real-world conditions. Although social aspect is not embedded as an objective function in the proposed optimization model, the integrating LIR decisions in the context of traffic-related disruptions will include customer satisfaction regarding the social dimension. In other words, optimizing environmental effects, freshness, and costs undoubtedly improve the customer satisfaction. On the other hand, pricing of perishable products and the longevity of these products have been important and effects on the demand function (Zulvia et al. 2020). Therefore, the present study addresses a multi-period, multi-product, multi-level, multi-objective LIR problem by considering dynamic pricing and dynamic transportation as a resilient strategy to overcome disruptions with related traffic conditions and related time windows. In addition, a novel hybrid method is proposed for solving the mixed-integer nonlinear optimization model. The findings of this study will be of great use to both scientists and engineers in the realm of perishable food supply chain. The general framework of this paper is illustrated in Fig. 1.

In summary, major contributions of this research can be described as follows:

- Proposing a bi-objective mathematical model for designing a resilient sustainable food supply chain network (RSFSCN), respecting perishability.
- This study considers a dynamic pricing strategy with related traffic condition and related time window under disruptions along with considering the shelf-time of products.

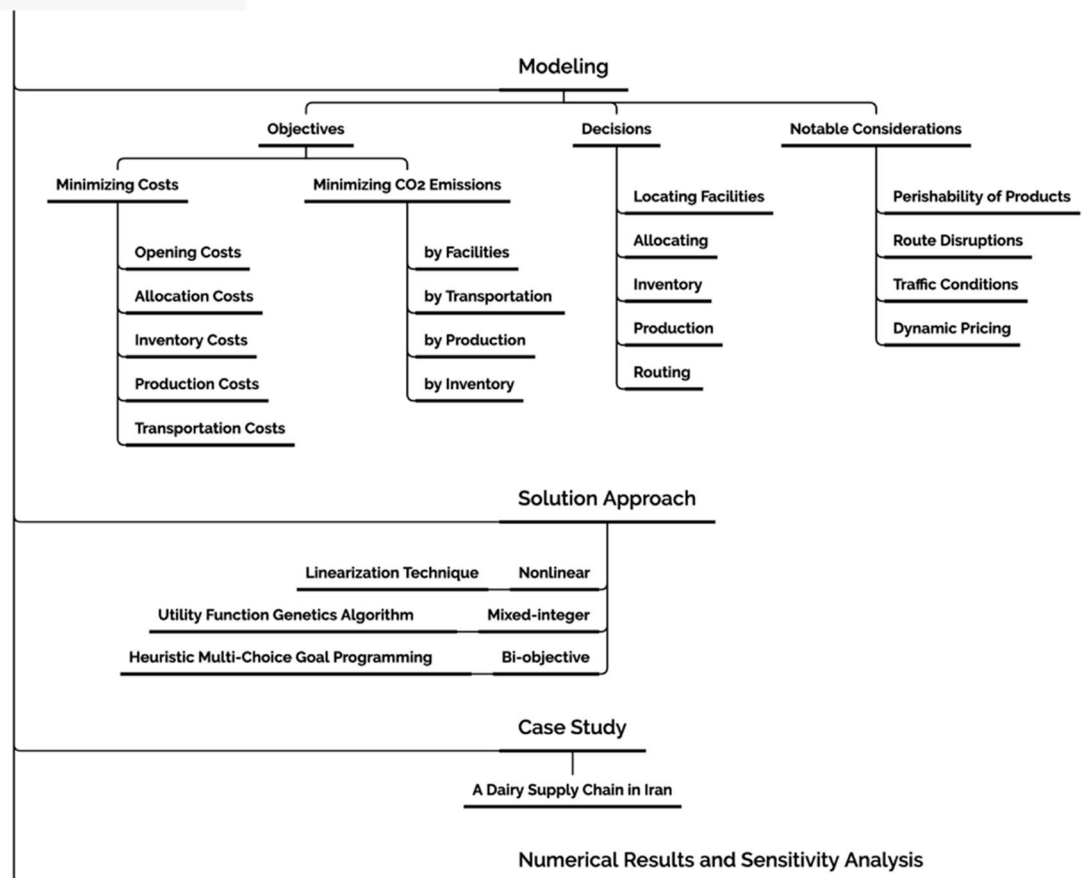**Designing a Resilient Sustainable Perishable Food Supply Network**

Fig. 1 The research framework

- This study applies a novel efficient hybrid solution method based on the Heuristic Multi-Choice Goal Programming and Utility Function Genetics Algorithm (HMCGP-UFGA).

After reviewing some relevant papers in "Literature review," the optimization model as well as the proposed hybrid solution method is presented in "Problem statement." In "Case study," we present a case study and apply the proposed approach. "Managerial implications" provides managerial implications by a comparative study. Finally, conclusion and future research directions can be found in "Conclusions."

Literature review

Food supply chains are progressively addressed by academic and industrial drivers involved in managing changes caused by various conditions, including extreme weather and economic and political conditions (Ivanov et al. 2015;

Tendall et al. 2015). The impact of strategic level flexibility on design decisions is therefore identified as one of the substantial factors for a food supply network to guarantee its resiliency and continuousness (Bourlakis and Weightman 2008; Nayeri et al. 2022). In the concept of food supply chains, controlling the quality of production, inventory management, and selecting pricing policy are determined as highly important concerns (Buisman et al. 2019). Raafat (1991) and Sazvar et al. (2013) reviewed the primary models of inventory management considering the deterioration of products. Wang et al. (2019) put forth an inventory control approach in a two-echelon fresh food network and performed different restocking strategies under certain conditions.

One of the striking aspects of a food supply chain discussion is designing a sustainable food supply network that has recently been contemplated by different investigators. Costa et al. (2014) addressed a sustainable supply chain of perishable vegetables by considering some technical-ecological constraints. They employed a two-stage stochastic programming approach to deal with demand uncertainties.

Zhang et al. (2019) used a MILP model for a closed-loop supply network with consideration of returnable transportation in a food supply chain to improve sustainable development. The primary goal was to raise the total profit of the holistic system. Meneghetti and Monti (2015) worked on the optimization of automated storage and retrieval (ASR) systems of goods requiring refrigerators by using constraint programming (CP), and by considering energy consumption and CO_2 emission. Saif and Elhedhli (2016) developed a mixed-integer optimization model minimizing costs and emissions of an eco-friendly supply chain and applied two case studies of perishable goods, including vaccines and meat. Biuki et al. (2020) formulated a mixed-integer mathematical model for LIR problems to design a sustainable supply chain of perishable products with uncertain demand. They solved the optimization problem by a hybrid method including particle swarm optimization (PSO) and genetic algorithm (GA). The important result of their research is that improving sustainability dramatically increases costs. In another research, a multi-objective linear programming model was developed to plan a sustainable agro-food supply network (Sazvar et al. 2018). They discovered that the more organic products supply chains contain, the more social satisfaction the supply chain encounters. The importance of organic food products is also tractable for enhancing the environmental efficiency of the supply chain. Recently, De and Bhattacharya et al. (2022) studied a pollution-sensitive Marxian production inventory model for deteriorating products under uncertain conditions. They applied a pollution generation model to calculate the environmental emission of a production system. As well, to address the pollution of supply chains, Bhattacharya and De (2021a, b) and Bhattacharya et al. (2022) applied a game theoretic approach to determine optimal logistics solutions.

Based on the aforementioned papers, logistics and transportation system management play a fundamental role in the supply chain management of perishable products due to their limited lifetime (Ghorbani and Jokar 2016). Concerning perishable products, several investigators have examined their inventory management in a food supply chain (Chen et al. 2014; Hsieh and Dye 2017; Herbon and Ceder 2018; Li and Teng 2018). Likewise, the perishability of goods is a significant issue in the LIR problem, which indicates that the quality of items decreases over time and that they are no longer usable once their expiration date has passed. Although limited papers have addressed LIR problems considering the perishability of goods, many scholars integrated inventory and routing decisions for perishable products (Soysal et al. 2018; Indah Saragih et al. 2019; Karakostas et al. 2019; Qiu et al. 2019). Rahimi et al. (2017) developed an optimization model with some objective functions to cope with the perishability of products in an inventory-routing problem. They used GA to attain satisfactory solutions in an acceptable

time horizon. Hu et al. (2018) integrated inventory and routing problems regarding perishable products to minimize transportation and energy costs. In another research, integration of inventory and routing problems is addressed regarding the perishability of goods in supply chains to minimize inventory costs and green gas emissions (Alkaabneh et al. 2020). Several heuristic models are employed by Alvarez et al. (2020) to solve the inventory-routing (IR) problem for decaying goods to find a near-optimal solution in a reasonable time, especially for large-size problems. The IR problem in a supply chain of foods was noticed by Li et al. (2018) to maximize the average food quality and minimize the total cost of production, inventory, and transportation. Among the above studies, a few research works have analyzed the LIR problem for perishable products. For example, Rafie-Majd et al. (2018) formulated the LIR problem in a supply network of perishable products with three echelons of suppliers, several distribution centers, and retailers. Zhao and Ke (2017) analyzed the LIR problem in a waste logistics network to minimize the risk and the environmental impacts as well as the total cost. Navazi et al. (2021) developed a mathematical model for a Closed-Loop Location-Routing-Inventory Problem (CL-LRIP). They embedded some real-world conditions in the developed model such as applying multi-compartment trucks with simultaneous pickup and delivery, and the risk of urban traffic.

On the other hand, many researchers have focused on integrating inventory and pricing decisions into supply chains. Maihami et al. (2019) addressed the inventory control and pricing of deteriorating products in a three-echelon supply chain by four strategies and developed a heuristic method to find the optimal solution. By considering the expiration date–based pricing (EDBP) policy, Vahdani and Sazvar (2022) examined a coordinated dynamic pricing and inventory control problem for a perishable product by considering social learning.

With contemplating the distribution of perishable food supply chain, adopting risk mitigation policies is important to confront disruption. Resilient supply chain design is therefore an extensively prominent approach to tackling disruptive events in supply chains. Resilience can be defined as applying a set of strategies to decrease the vulnerability of a supply chain. The prevailing policies to mitigate the impact of disruption in designing a resilient supply network are as follows: (i) holding excess stock (Garcia-Herreros et al. 2014; Kristianto et al. 2014), (ii) facility fortification (Hasani and Khosrojerdi 2016; Jabbarzadeh et al. 2016a), (iii) applying backup suppliers (Hasani and Khosrojerdi 2016; Madadi et al. 2014; Sadghiani et al. 2015), (iv) twice allocation (Cui et al. 2010; Zahiri et al. 2017), and (v) multi-sourcing (Azad et al. 2014; Hasani and Khosrojerdi 2016). Besides, numerous investigations reveal that varied studies have examined diverse resiliency techniques (Nooraie and Parast 2016;

Jabbarzadeh et al. 2016b). These studies implied several proactive and reactive resiliency policies. Ivanov et al. (2015) similarly analyzed various proactive and reactive strategies for reconfiguration of the network throughout a dynamic and a linear optimization model. Furthermore, a multi-stage stochastic optimization model was developed for a generic supply network by Fattahi et al. (2017). They concluded that reactive strategies besides fortification plans can mitigate the lost capacity after disruptive events. Saha et al. (2020) evaluated demand substitution and backorder offer to tackle supply disturbance.

Finally, dairy supply chains are one of the most important perishable supply chains, especially in the recent food crisis era, which are the target of this paper. Shafiee et al. (2021) proposed a multi-objective model to minimize the total costs and environmental impacts and maximize the social impacts of a multi-period and multi-product chain from the dairy industry, by emphasizing on the delivery time and the First-In First-Out (FIFO) warehouse management. To solve the proposed model, a hybrid method based on a heuristic algorithm and the augmented ε-constraint method was developed. Validi et al. (2014) concentrated on a dairy distribution network to minimize overall costs and CO_2 emissions of a food supply network using GA. However, their model has not directly addressed the perishability of goods. Table 1 reviews most related papers to the topic of this paper.

Although several studies have explored PFSCN, there are still several research gaps in this area. To the best of our knowledge, despite the real-world significance of designing a sustainable resilient food supply chain considering perishability and dynamic pricing, no study has explored it in the PFSCN problem so far. Furthermore, as a major constraint, traffic condition–related time windows have rarely been addressed in the previous studies.

To fill in these research gaps, in this study, a novel multi-objective MINLP is suggested to design a resilient sustainable PFSCN considering LIR decisions, traffic-related time windows, perishability of products, and dynamic pricing policy. The proposed model implicitly addresses the social

aspect of sustainability by enhancing customer satisfaction with better pricing and freshness of the products. A real dairy supply chain in Iran is selected as a case study to analyze the results. Based on the literature, some prominent features that distinguish this paper from the existing research are as follows:

– First, while there is a broad range of studies dedicated to the LIR problem, to the best of our knowledge, this paper might be the first attempt at analyzing the LIR concept for designing RSPFSN with perishable products and dynamic pricing policy under disruptions, which is highly significant from theoretical and practical viewpoints.
– Second, in this research some new considerations such as dynamic pricing strategy and traffic-related time windows along with supply chain resiliency and limited shelf-time of products are taken into account, inspired by the real world, thus contributing to the RSPFSN literature.
– Third, this research proposes a new hybrid algorithm (HMCGP-UFGA) to find optimal solutions especially in the case of large-size problems. Applying the proposed algorithm for a real case of the dairy industry in Iran approves its accuracy and applicability.

Problem statement

As stated in "Introduction," this study focuses on LIR decision-making strategies for perishable food supply chains under a resilient strategy to reduce disruptions of traffic conditions related to time windows under considering the longevity of perishable products. It incorporates dynamic pricing and transportation policies to minimize costs as well as environmental impacts. For this purpose, we consider a perishable food supply chain including production centers (PCs), distribution centers/warehouses (DCs/W), and retailers. Through this supply network, products are transferred from PCs to DCs and from DCs to retailers (see Fig. 2).

Table 1 Relevant research works

Paper	SC	Resilience	Sustainability	Approach	Problem
(Shafiee et al. 2021)	Dairy SC	No	Yes	Multi-objective robust OPT	Inventory and production
(Costa et al. 2014)	Vegetable SC	No	Yes	Multi-stage stochastic OPT	Network design
(Saif and Elhedhli 2016)	Vaccine SC	No	Yes	Mixed-integer OPT	LIR
(Jabbarzadeh et al. 2016b)	Closed-loop SC	Yes	No	Robust OPT	Network design
(Yavari et al. 2020)	Food SC	Yes	No	Mixed-integer OPT	LIR
(Sazvar et al. 2018)	Food SC	No	Yes	Multi-objective OPT	Network design
(Jouzdani and Govindan 2021)	Dairy SC	No	Yes	Multi-objective OPT	Network design
(Talouki et al. 2021)	Perishable SC	No	Yes	Robust OPT	Transportation

There are various routes for transferring to retailers. These routes are subject to traffic disruption. Each route starts from candidate DCs, and after delivering the product to one or more retailers, it returns to the candidate DCs. Different vehicles with different capacities can be used for transportation. If an order is received at the start of period (t), it will be expired at the start of period ($t + LF_p$), where LF_p represents the product's lifetime.

In this paper, we intend to determine the location of DCs and allocate the optimal route according to the traffic disturbance related to the time window, optimal inventory levels according to the product longevity, and allocation of retailers to the DCs, and the DCs to the manufacturer. Finally, we want to determine the selling price of perishable products according to the product longevity in different scenarios of traffic disruption. The major objective of this research is the minimization of overall costs and environmental impacts of the supply chain.

Optimization model

This section introduces indices, decision variables, parameters, and ultimately the proposed optimization model based on the assumptions expressed below.

Assumptions

In order to model the considered RSPFSN problem, the following assumptions are considered:

1. According to the literature, the use of refrigerated vehicles for transporting perishable products is usual (Song and Ko 2016; Jouzdani and Govindan 2021). This research also assumes that all types of vehicles are equipped with refrigerators.
2. It is necessary to note that the quality of the product will be affected when it does not get to its destination on time even if the product is transferred with vehicles equipped with refrigerators. The reason is that vehicles' doors get opened and closed several times to put or take out products, which alters the temperature of the container, leading to a decrease in the freshness of products (Song and Ko 2016). Therefore, products are perishable even when they are in a vehicle equipped with a refrigerator.
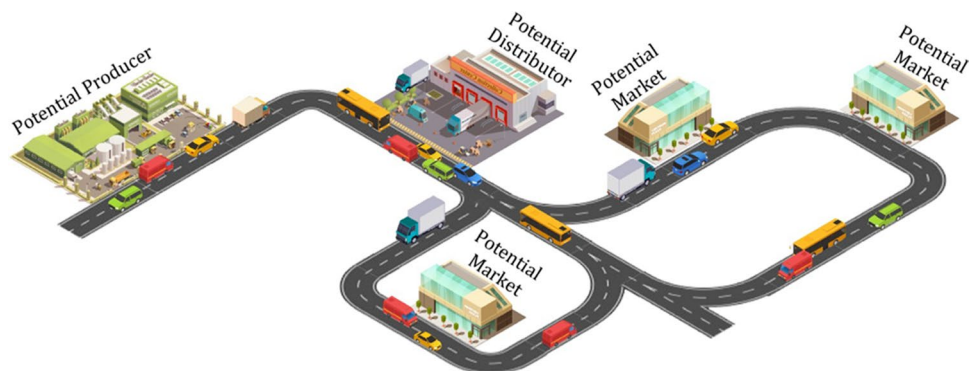3. There are several different perishable products with different lifespans.
4. Similar to Yavari et al. (2020), the amount of demand from retailers varies over time, depending on the freshness and price of the products.
5. Similar to Zulvia et al. (2020), the environmental aspect is evaluated by the total amount of CO_2 emitted by transportation, inventory, and production processes.
6. The travel time is not constant and calculated by the speed, the distance of trips, and the traffic conditions.
7. Similar to Yavari et al. (2020), this paper considers the price function based on the retailers' price given the product longevity.
8. Price-susceptible demand and zonular price function entailing the product longevity (day), adapted from Adenso-Díaz et al. (2017).
9. The shortage is not allowed.

Proposed mathematical model

Sets and indices:

N The set of existent routes

R The set of retailers, $r = \{1, 2, 3, \ldots, R\}$

P The set of products, $p = \{1, 2, 3, \ldots, P\}$

T The set of periods, $t = \{1, 2, 3, \ldots, T\}$

V The set of vehicles, $v = \{1, 2, 3, \ldots, V\}$

D The set of potential locations for DCs, $d = \{1, 2, 3, \ldots, D\}$

Fig. 2 The proposed network problem

M   The set of PCs, $m = \{1, 2, 3, \ldots, M\}$

Parameters:
Cost parameters ($\$$):

FC_{mt} Fixed cost of opening PC m at period t

FC_{dt} Fixed cost of opening DC d at period t

FC_{dmt} Fixed cost of allocation DC d to PC m at period t

FC_{rdt} Fixed cost of allocating retailer r to DC d at period t

SC_{mdvt} Shipping cost from PC m to DC d with vehicle v at period t

SC_{drvt} Shipping cost from DC d to retailer r with vehicle v at period t

CHI_{dt} Cost of holding inventory in DC d at period t

PC_{pmt} Production cost of product p in PC m at period t

CF_{vt} Fuel cost of vehicle v by considering traffic condition at period t

Environmental parameters (ton):

RE_{mt} CO_2 emission rate due to opening PC m at period t

RE_{dt} CO_2 emission rate due to opening DC d at period t

RE_{pdt} CO_2 emission rate due to holding product p in DC d at period t

RE_{pmdvt} CO_2 emission rate due to transporting product p from PC m to DC d with vehicle v at period t

RE_{pdrvt} CO_2 emission rate due to transporting product p from DC d to retailer r with vehicle v at period t considering traffic condition

RE_{vrt} Rate of CO_2 emission at restarting vehicle v in retailer r at period t

RE_{pmt} CO_2 emission rate due to producing product p in PC m at period t

Other parameters:

MD_{prt}(kg)   Maximum demand of products p in retailer r at period t

$MS_{drvt}\left(\frac{km}{h}\right)$ The maximum speed allowed with considering traffic condition on the existing routes from DC d to retailer r with vehicle v at period t

Ds_{dr}(km)   The distance between DC d and retailer r

C_v(kg)   Capacity of vehicle v

CD_d (kg)   Capacity of DC d

CP_m(kg)   Capacity of PC m

$PE_{rpt}\left(\frac{kg}{\$}\right)$ Demand elasticity of retailer r for product p at period t

STL_{rvt}(h)   Late service time of retailer r at period t by vehicle v

STE_{rvt}(h)   Early service time of retailer r at period t by vehicle v

LST_{rvt}(h)   Service time of latest for retailer r at period t by vehicle v

EST_{rvt}(h)   Service time of earliest for retailer r at period t by vehicle v

RCF_{vdrt} C(l/h)   Consumption rate of fuel for vehicle v while delivering product from DC d to retailer r under traffic condition at period t

M A large number

RVD_{ndt} 1 if route n goes to DC d at period t, otherwise 0

RVR_{nrt} 1 if route n goes to retailer r at period t, otherwise 0

LF_p (day)   The lifespan of product p

Decision variable:

SL_{rvt}(h)	Service level of retailer r with vehicle v at period t	USP_{prt}($)	The sale price of product p in retailer r at period t
AT_{vrt}(h)	The time of arriving vehicle v to retailer r at period t	IL_{prt}(kg)	Inventory level of product p in retailer r at period t
DT_{vrt}(h)	The time of leaving vehicle v from retailer r at period t	OD_{dt}	1 if DC d at period t is opened, otherwise 0
		OP_{mt}	1 if PC m at period t is opened, otherwise 0
AD_{rpt}(kg)	The actual demand of retailer r for product p at period t affected by pricing	γ_{rdt}	1 if retailer r is allocated to DC d at period t, otherwise 0
Xpd_{pmdvt}(kg)	The amount of product p transported from PC m to DC d with vehicle v at period t	δ_{dmt}	1 if DC d is allocated to PC m at period t, otherwise 0
Xdr_{pdrvt}(kg)	The amount of product p transported from DC d to retailer r with vehicle v at period t	μ_{vnt}	1 if vehicle v is selected for route n at period t, otherwise 0
Xp_{pmt}(kg)	The amount of product p produced in PC m at period t	Y_{nvrt}	1 if route n is used by vehicle v delivering to retailer r starting at period t, otherwise 0
I_{pdt}(kg)	The inventory level of product p in DC d at period t	Z_{nt}	1 if route n is selected at period t, otherwise 0
SP_{prt}($)	Maximum sale price of product p in retailer r at period t		

Objective functions

$$
\begin{aligned}
\min Z_2 = {} & \sum_{p=1}^{P} \sum_{m=1}^{M} \sum_{d=1}^{D} \sum_{r=1}^{R} \sum_{v=1}^{V} \sum_{t=1}^{T} Ds_{dr}.MS_{drvt}.\left(RE_{vrt} + Xpd_{pmdvt}.RE_{pmdvt} + Xdr_{pdrvt}.RE_{pdrvt}\right) \\
& + \sum_{p=1}^{P} \sum_{d=1}^{D} \sum_{t=1}^{T} RE_{pdt}.I_{pdt} + \sum_{m=1}^{M} \sum_{t=1}^{T} RE_{mt}.OP_{mt} + \sum_{d=1}^{D} \sum_{t=1}^{T} RE_{dt}.OD_{dt} \\
& + \sum_{p=1}^{P} \sum_{m=1}^{M} \sum_{t=1}^{T} RE_{pmt}.Xp_{pmt}
\end{aligned}
\tag{1}
$$

$$
\begin{aligned}
\min Z_1 = {} & \sum_{m=1}^{M} \sum_{t=1}^{T} FC_{mt}.OP_{mt} + \sum_{d=1}^{D} \sum_{t=1}^{T} FC_{dt}.OD_{dt} + \sum_{d=1}^{D} \sum_{m=1}^{M} \sum_{t=1}^{T} FC_{dmt}.\delta_{dmt} + \sum_{r=1}^{R} \sum_{d=1}^{D} \sum_{t=1}^{T} FC_{rdt}.\gamma_{rdt} \\
& + \sum_{p=1}^{P} \sum_{m=1}^{M} \sum_{t=1}^{T} PC_{pmt}.Xp_{pmt} + \sum_{p=1}^{P} \sum_{d=1}^{D} \sum_{t=1}^{T} CHI_{dt}.I_{pdt} \\
& + \sum_{p=1}^{P} \sum_{m=1}^{M} \sum_{d=1}^{D} \sum_{v=1}^{V} \sum_{n=1}^{m\cup d} \sum_{t=1}^{T} SC_{mdvt}.Xpd_{pmdvt} + \sum_{p=1}^{P} \sum_{d=1}^{D} \sum_{r=1}^{R} \sum_{v=1}^{V} \sum_{n=1}^{r\cup d} \sum_{t=1}^{T} SC_{drvt}.Xdr_{pdrvt} \\
& + \sum_{d=1}^{D} \sum_{r=1}^{R} \sum_{n=1}^{r\cup d} \sum_{v=1}^{v} \sum_{t=1}^{T} Y_{nvrt}.CF_{vt}.RCF_{vdrt}.\left(\frac{Ds_{dr}}{Ms_{drvt}}\right)
\end{aligned}
\tag{2}
$$

Constraints:

$$
Xp_{pmt} = \sum_{d=1}^{D} \sum_{v=1}^{V} Xpd_{pmdvt} \qquad \forall m, p, t \tag{3}
$$

$$
I_{pd(t-1)} + \sum_{m=1}^{M} \sum_{v=1}^{V} Xpd_{pmdvt} = \sum_{v=1}^{V} \sum_{r=1}^{R} Xdr_{pdrvt} + I_{pdt} \; \forall p, d, t \tag{4}
$$

$$
\sum_{d=1}^{D} \sum_{v=1}^{V} Xdr_{pdrvt} + IL_{pr(t-1)} = AD_{prt} + IL_{prt} \qquad \forall p, r, t \tag{5}
$$

$$
\sum_{p=1}^{P} I_{pdt} \leq CD_d.OD_{dt} \qquad \forall d, t \tag{6}
$$

$$
\sum_{p=1}^{P} Xp_{pmt} \leq CP_m.OP_{mt} \qquad \forall m, t \tag{7}
$$

$$I_{pd(t-1)} \leq \sum_{r=1}^{R} \sum_{t' \geq t}^{t' \leq (t+LF_p)} AD_{prt'} \cdot \gamma_{rdt'} \qquad \forall p, d, t \qquad (8)$$

$$IL_{pr(t-1)} \leq \sum_{t' \geq t}^{t' \leq (t+LF_p)} AD_{prt'} \qquad \forall p, r, t \qquad (9)$$

$$\sum_{m=1}^{M} Xp_{pm(t-1)} \leq \sum_{t' \geq t}^{t' \leq (t+LF_p)} AD_{prt'} \qquad \forall p, t \qquad (10)$$

$$\sum_{p=1}^{P} \sum_{m=1}^{M} \sum_{d=1}^{D} Xpd_{pmdvt} \leq C_v \cdot \mu_{vnt} \quad \forall v, n, t \qquad (11)$$

$$\sum_{p=1}^{P} \sum_{d=1}^{D} \sum_{r=1}^{R} Xdr_{pdrvt} \leq C_v \cdot \mu_{vnt} \quad \forall v, n, t \qquad (12)$$

$$\sum_{p=1}^{P} \sum_{v=1}^{V} Xdr_{pdrvt} \leq M \cdot \gamma_{rdt} \quad \forall r, d, t \qquad (13)$$

$$\sum_{p=1}^{P} \sum_{v=1}^{V} Xpd_{pmdvt} \leq M \cdot \delta_{dmt} \quad \forall m, d, t \qquad (14)$$

$$\gamma_{rdt} \leq OD_{dt} \ \ \forall r, d, t \qquad (15)$$

$$\delta_{dmt} \leq OD_{dt} \ \ \forall d, m, t \qquad (16)$$

$$\delta_{dmt} \leq OP_{mt} \ \ \forall d, m, t \qquad (17)$$

$$\sum_{d=1}^{D} \gamma_{rdt} \leq 1 \ \ \forall t, r \qquad (18)$$

$$\sum_{m=1}^{M} \delta_{dmt} \leq 1 \ \ \forall t, d \qquad (19)$$

$$AD_{prt} = MD_{prt} - PE_{prt} \cdot USP_{prt} \ \ \forall p, r, t \qquad (20)$$

$$USP_{prt} = \left(USP_{pr(t-1)} - \frac{SP_{prt}}{LF_p} \right) \cdot \left(1 - \sum_{d=1}^{D} \gamma_{rdt} \right) + SP_{prt} \cdot \left(\sum_{d=1}^{D} \gamma_{rdt} \right) \ \ \forall p, r, t \qquad (21)$$

$$SL_{rvt} \leq \frac{1 + 0.15 \left(\frac{DT_{vrt} - AT_{vrt}}{C_v} \right)^4 - STL_{rvt}}{LST_{rvt} - STL_{rvt}} \ \ \forall r, v, t \qquad (22)$$

$$SL_{rvt} \geq \frac{STE_{rvt} - 1 + 0.15 \left(\frac{DT_{vrt} - AT_{vrt}}{C_v} \right)^4}{STE_{rvt} - EST_{rvt}} \ \ \forall r, v, t \qquad (23)$$

$$\sum_{n=1}^{r \cup d} Z_{nt} \cdot RVR_{nrt} \leq 1 \ \ \forall r, t \qquad (24)$$

$$Z_{nt} \leq \sum_{d=1}^{D} RVD_{ndt} \cdot OD_d \ \ \forall n, t \qquad (25)$$

$$DT_{vrt} \leq AT_{vrt} + \sum_{d=1}^{D} \frac{DS_{dr}}{Ms_{drvt}} \cdot \left(1 + 0.15 \left(\frac{DT_{vrt} - AT_{vrt}}{C_v} \right)^4 \right) + M \cdot (1 - Y_{nvrt}) \ \ \forall v, r, t, n \qquad (26)$$

$$DT_{vrt} \geq AT_{vrt} + \sum_{d=1}^{D} \frac{DS_{dr}}{Ms_{drvt}} \cdot \left(1 + 0.15 \left(\frac{DT_{vrt} - AT_{vrt}}{C_v} \right)^4 \right) - M \cdot (1 - Y_{nvrt}) \ \ \forall v, r, t, \qquad (27)$$

$$AT_{vrt} \geq STL_{rvt} \ \ \forall v, r, t \qquad (28)$$

$$DT_{vrt} \leq STE_{rvt} \ \ \forall v, r, t \qquad (29)$$

$$\sum_{n=1}^{N} \mu_{vnt} \leq M \cdot Z_{nt} \ \ \forall n, t \qquad (30)$$

$$\sum_{r=1}^{R} Y_{nvrt} \leq M \cdot \mu_{vnt} \ \ \forall v, n, t \qquad (31)$$

Objective functions:

Equation (1) is the first objective of minimization of the total cost including the fixed cost of opening the facility, the fixed cost of allocation, the cost of production, the cost of holding inventory, the cost of transportation, and the cost of vehicle fuel due to the traffic conditions respectively. Equation (2) shows the second objective function, minimizing the total amount of CO_2 emissions, which includes the amount of CO_2 emissions depending on traffic conditions and transportation between facilities as well as the amount of CO_2 emitted through holding products in the DCs, opening facilities, and production processes respectively.

Flow constraints:

Constraints (3) to (5) indicate that the amount of input and output of facilities must be equal.

Capacity constraints:

Constraints (6) and (7) indicate the inventory capacity constraint at distributers and the production capacity constraint of manufacturing respectively. As well, constraints (11) and (12) guarantee the capacity of vehicles.

Social constraints:

Constraints (8) to (10) avoid producing and holding inventories more than requirements to decrease the amount of expired food.

Allocation constraints:

Constraints (13) and (14) ensure that flow is zero between unallocated pairs. According to constraints (15) to (17), allocation must be attributed to established facilities. Constraint (18) (constraint (19)) ensures that a retailer (distributor) can be allocated to a maximum of one distributor (manufacturer).

Pricing constraints:

Constraints (20) to (21) are inspired by Adenso-Díaz et al. (2017) and Afshar-Nadjafi (2016) to demonstrate the performance of price dynamics that depends on the longevity of the product as well as the sensitivity of demand to price. In general, these constraints indicate the relation among demand, price, price dynamics function, and longevity of products. On the other hand, constraint (21) indicates the dependence of each DC service on retailer demand, which occurs when allocation is made.

Time windows constraints:

Constraints (22) to (29) show the level of retailer's service with respect to the $t(X) = t_0 \left(1 + 0.15\left(\frac{x}{k}\right)^4\right)$ in the time window where $t(X)$ is the logit function, t_0 is the beginning travel time, k is the capacity of vehicles, and x is the travel time (Zulvia et al. 2020). These constraints indicate the service level at arrival and departure time based on traffic conditions, expressing the best service level to retailers at the time of the first service and the time of the last service because of randomness in service time. Constraints (26) and (27) calculate the time for each node to get the vehicle that will carry products along the road, with the traveled distance of routes determined by the vehicle's speed. Upper bounds and lower bounds of time windows, specifying the service level provided by the retailer, are known as constraints (28) and (29) respectively.

Linearization

The model developed above is categorized as a mixed-integer nonlinear optimization (MINLO) model due to some nonlinear expressions such as constraints (8), (21), (22), (23), (26), and (27). The linear equivalents of the last four constraints cannot be formulated. However, there are various methods in the literature to turn constraints (8) and (21) into linear ones. For example, Eq. (32) shows the linearization techniques used by several researchers such as Gholizadeh et al. (2020a). To address a nonlinear term in the form of

$X_1 * X_2$ where X_1 is a binary variable and X_2 is a continuous variable, we can use variable $Z = X_1 * X_2$. When X_1 is equal to 1, then $Z = X_2$. Otherwise, $Z = 0$. Hence, the inequalities (32) need to be added to the model.

$$\begin{aligned} Z &\leq X_2 \\ Z &\leq MX_1 \\ Z &\geq X_2 - M.(1 - X_1) \end{aligned} \tag{32}$$

Solution method

In this section, we will introduce the solution methods used in this article. As mentioned in the previous sections, this paper employed a new hybrid method based on HGAMCGP-UF. The multi-choice goal programming with utility function (MCGP-UF) has been used to change the multi-objective model into a single-objective model. On the other hand, due to the complexity of the problem, a GA and a heuristic method have been used. According to the recent literature, some researchers have combined various types of goal programming with GA (e.g., Moradgholi et al. 2016). But the most main difference of the proposed method in this paper is the combination of the heuristic algorithm with MCGP-UF and the GA. We first combine the heuristic method with the MCGP-UF and then incorporate it into the GA.

MCGP-UF

Goal programming (GP) is a prevailing approach for solving multi-objective models. There are different versions of GP such as weighted GP, Multi-Choice GP (MCGP), Meta GP, and MCGP with Utility Function (MCGP-UF). In this paper, the MCGP-UF method, introduced by Chang (2011), is applied to develop a solution approach for the proposed model. The main advantage of this method over the other versions of GP is incorporating experts' opinions on the problem (Jadidi et al. 2015). The corresponding formulation is as follows (Chang 2011):

MCGP-UF to solve the SR-SCND model
$Min \ \sum_k \left[w_k^d.(d_k^+ + d_k^-) + w_k^\xi.(\xi_k^-) \right]$
$s.t.$
$\lambda_k \leq \dfrac{U_{k,max} - y_k}{U_{k,max} - U_{k,min}}$
$f_k(X) + d_k^- - d_k^+ = y_k$
$\lambda_k + \xi_k^- = 1$
$U_{k,min} \leq y_k \leq U_{k,max}$
$d_k^+, d_k^-, y_k, \lambda_k, \xi_k^- \geq 0$
Model constraints set

(33)

In the above model, $U_{k,\,\max}$ and $U_{k,\,\min}$ represent the upper and lower bounds of the kth objective aspiration level, respectively. y_k is a continuous variable where d_k^+ and d_k^- are the positive and negative deviations of $f_k(X)$ from y_k. λ_k shows utility values and ξ_k^- shows the normalized deviation of y_k from $U_{k,\,\min}$. It should be noted that the model can be normalized as follows (if needed):

$$\text{Min} \sum_k \left[w_k^d \cdot \left(\frac{d_k^+ + d_k^-}{f_k^- - f_k^+} \right) + w_k^\xi \cdot \left(\xi_k^- \right) \right] \tag{34}$$

In the above equation, for the minimization objective functions, $f_k^+ = \left\{ \min f_k(X) \right\}$ and $f_k^- = \left\{ \max f_k(X) \right\}. \xi_k^-$ do not need to be normalized because $0 \le \xi_k^- \le 1; \forall k$.

Heuristic method

Besides the MCGP-UF method, we provide a heuristic method for the proposed model to decrease computations significantly. The heuristic algorithm is based on relaxing binary variables. The steps of the heuristic method are as follows:

1. The constraints with binary variables must be relaxed. We assume the binary variables related to allocating and opening facilities (for example, OD_{dt}, OP_{mt}, γ_{rdt}, δ_{dmt}, μ_{vnt}) are non-negative variables so that the new formulation is a relaxation.
2. Solve the relaxation to optimality.
3. Record all non-zero quantities of the relaxed variables obtained from relaxed model results.
4. Set each strictly positive value of the relaxed variables to 1, and add them as constraints to the main model.
5. Solve to optimality.

GA

Considering the reported efficiency of GAs for a wide range of complex decision problems (Gholizadeh et al. 2020b), this study will adopt a customized GA as a solution approach. The first step in solving a problem with metaheuristic methods is to create an appropriate structure for potential solutions to the problem which randomly generates a set of practical solutions (population) and calculates the fitness function for each chromosome. Then, to improve the initial population, a new population is generated, using crossover and mutation operators. In selecting chromosomes, the proposed GA is using the method roulette wheel according to the proportionality of each chromosome with the objective function (fitness function).

Since each chromosome must have information about the routing, the retailers assigned to the DCs and the location of the DCs, as well as the allocation of the means of transport to the DCs, and retailers at each period, Fig. 3 shows an example of a chromosome string for 6 retailers, 3 DCs, 4

vehicles with different capacities, and 2 periods. As you can see, each chromosome is divided into 3 parts.

The first part shows the location of DCs and allocation decisions in each period. The second part shows the location of retailers and allocation decisions in each period. Finally, the third part deals with the allocation decisions for the vehicle to the DCs and retailers, which takes the optimal route. In the first part, each gene is related to the candidate location of DCs in a relevant period, and the value of the gene in this part is the number of retailers assigned to DCs in a specific period. For example, in period 1, DC 1 serves retailers 1, 2, and 3, or in the same period, DC 3 serves retailer 6. A value of zero means that in this period, no retailer is assigned to the DC. In the second part, the value of each gene is the place related to allocating DCs to retailers in order to prioritize routing. For example, in period 2, DC 3 serves to 5 retailers. According to the order route D3-4-6-2-5-3-D3, it is necessary to select the vehicle considering its capacity, which is described in the third part. The third part has two sections. The first one is allocating the vehicle to the DCs which are randomly assigned to each gene. Here, each idle vehicle is shown with zero. But in the second section, the allocation of the vehicle to the retailers for optimal routing is shown with the number of genes equal to the total number of retailers and the vehicle. In the first step, the number of genes is selected from the number of vehicles randomly, and then, the number of genes is selected from the number of retailers and the remaining vehicles and assigned.

Crossover In the world of evolutionary algorithms, the crossover operator improves the explorative behavior of the algorithm. From the proposed GA, the first step, we used here is single-point crossover. In the second step, a pair of preferred chromosomes randomly selected from sets consists of DCs and retailers for each string. Finally, the boundary points between each period in the second step help the child to practically inherit all the genes from the parents to the crossover point. Figure 4 shows an example of a crossover operator.

Mutation The mutation operator generally does an exploitative behavior to find a new neighbor of a solution. This is very important because it prevents the algorithm from staying in a local optimal solution, and, on the other hand, causes randomly searching in the solution space. If a gene can be any binary string, it can be easily mutated by a simple rule. However, if it needs to belong to a set, it can be mutated by choosing another chromosome from the set randomly. Alternately, a part of it can be mutated by choosing another element of that set. In this study, the mutation is applied to the third part of a chromosome, i.e., the allocation of the vehicle to DCs and retailers. Based on the period, if the chromosome is forced to allocate more DCs, Find your way in such a way that the optimal solution is available in the

Fig. 3 Chromosome representation
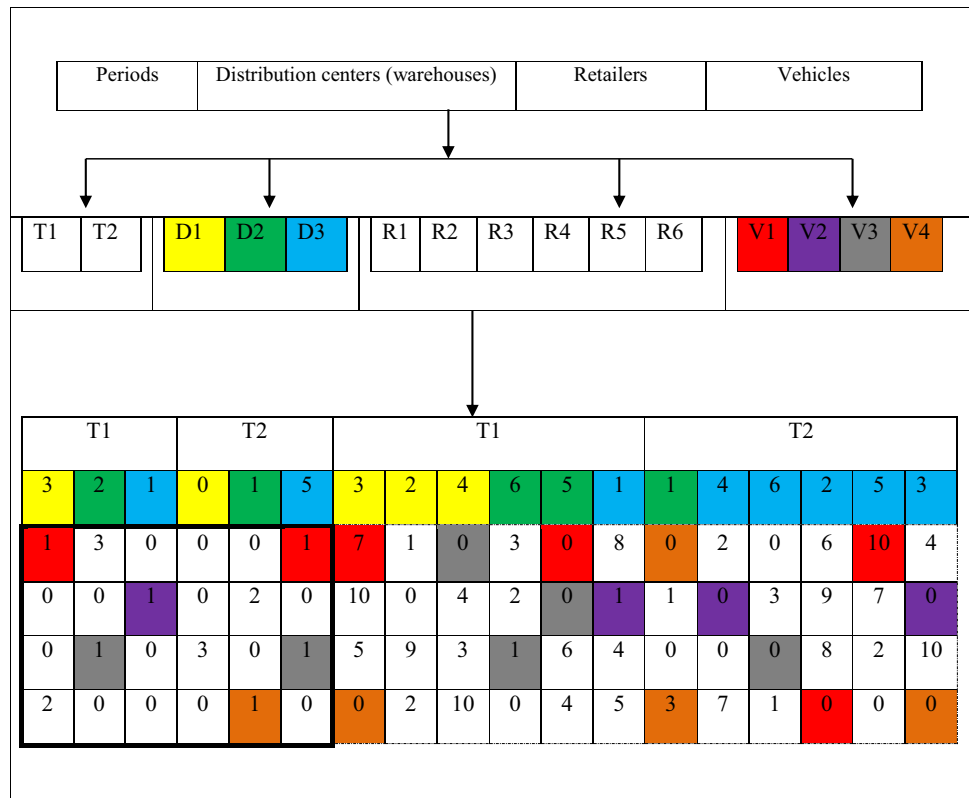
order of the retailers in another period. Figure 5 shows an example of a mutation operator.

Parameter setting

Here, we will discuss about the parameter's value of the proposed solution approach. Since incorrect adjustment causes inefficient behavior of the algorithm, the Taguchi technique is used to adjust the parameters (Fakhrzad et al. 2019; Rao et al. 2020). In this study, three levels for the algorithm parameters are considered and presented in Table 2.

To select the best level of parameters, "the larger value is better" is used to rank GA's parameters with respect to the signal-to-noise (S/N) ratio (Naderi et al. 2011). Figure 6 presents the S/N graphs for the experiments.

Fig. 4 Crossover operator
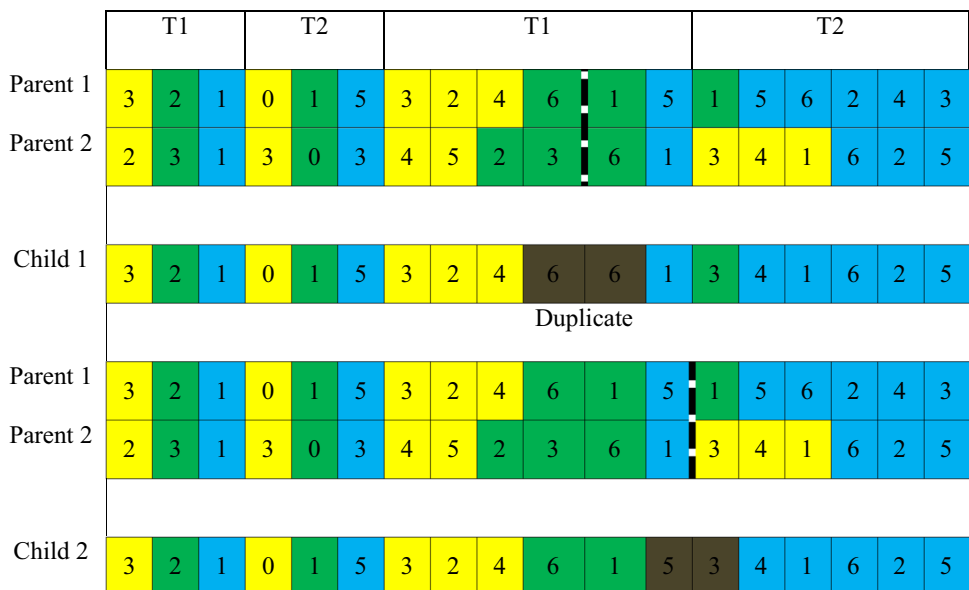
Fig. 5 Mutation operator
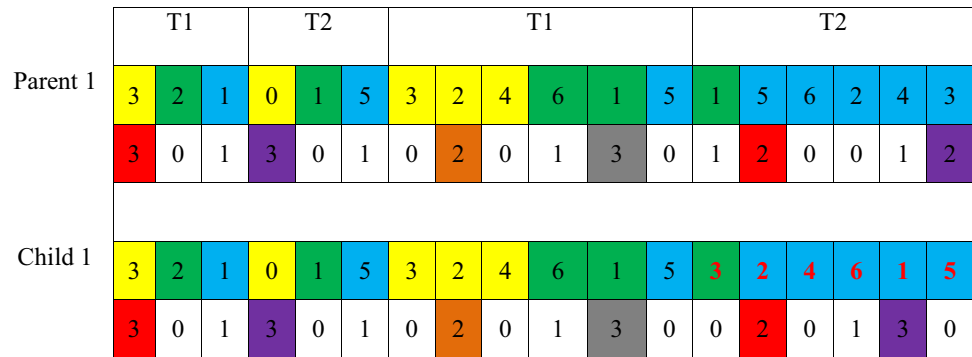
Table 2 Values of parameters for various levels

Algorithm	Parameter	Level 1	Level 2	Level 3
GA	Crossover probability	0.6	0.7	0.8
	Mutation probability	0.1	0.2	0.3
	Population size	100	170	250
	Maximum of iteration	150	250	350

The optimal level of each parameter of the algorithm is reported in Table 3.

Case study

Here, we conduct a case study to answer "how" and "why" questions in a real context to evaluate the proposed model and the impact of perishable food supply chain design parameters. As the consumption of dairy products is increasing rapidly, it is expected that the demand and production of these products will increase in the future, thus creating investment opportunities for organizations to design efficient chains. Therefore, to help the different stages of the study, including valuing the parameters, analyzing the results, and evaluating the objectives, in this study, we examine Kalleh Dairy which is an Iranian dairy, food, and drink company

Table 3 Optimal values of the proposed algorithm parameters

Algorithm	Parameter	Best level	Value
GA	Crossover probability	3	0.8
	Mutation probability	1	0.1
	Population size	1	100
	Maximum of iteration	1	150

headquartered in Amol, Iran. Kalleh Industrial Dairy Group (KIDG) is a well-known dairy product producer in Iran. In line with KIDG's development strategies and compliance with government regulations, KIDG seeks to improve its supply chain. Due to the geographical location of KIDG and due to the high volume of distribution of products in each city in the region, there is a potential place to establish DCs which serve one or more retailers.

In general, most parameters are collected from experts, documents, and databases of KIDG. It is also assumed that different vehicles, for example, heavy pickup, light truck, heavy truck, and trailer, are used to transport products. On the other hand, products in different packages have different lifespans, for example, milk products in plastic bags containing pasteurized milk, which is more sensitive to transportation and traffic conditions, and also have a lower price with a shorter lifespan and higher demand. On the other

Fig. 6 Mean S/N ratio at each level for GA
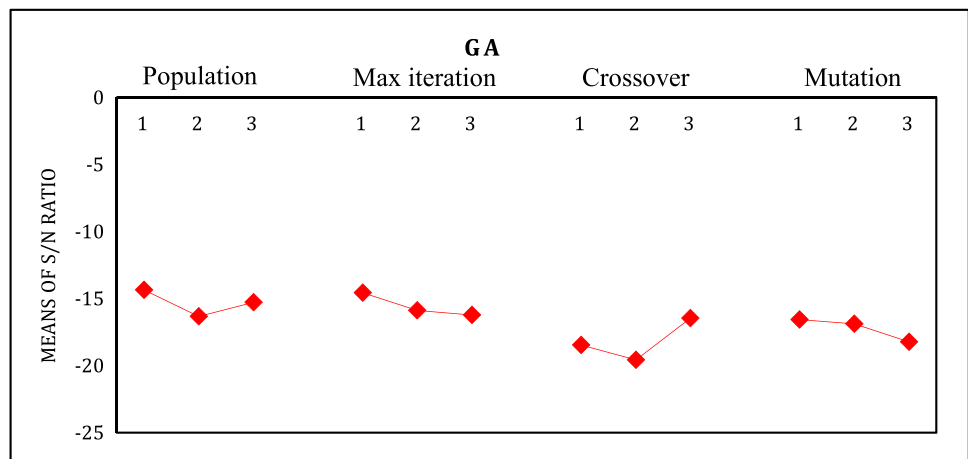
hand, milk products come in aseptic packages with a longer lifespan, lower sensitivity, and higher prices, resulting in lower demand. To show the reliability of the proposed model and the proposed algorithm, we first examine the problem in several different test problems in terms of the value of objectives, solution time, and the amount of deviation. This analysis for the suggested optimization model is implemented in the MATLAB 2013 software and GAMS 2017 software with solver BARON. All program runs are made on a PC with Intel(R) Core (TM) i5-5200U CPU @ 2.20 GHz under Windows 10. Due to company policies, it was not possible to extract information from it. Therefore, according to the behavior of KIDG data, we use a random distribution approximated according to real data of KIDG to implement the proposed approach. Table 4 shows generating real data according to the behavior of KIDG data.

Validation of the proposed model

In this section, 15 test problems are set to evaluate the performance of the model. Figure 7 and Table 5 illustrate that the proposed method can achieve optimal or near to optimal solutions at the best MCGP-UF time and the time of both methods is growing at roughly the same rate by increasing the dimension. The problem escalates to the point that for problems 12 to 15, the MCGP-UF cannot provide an optimal solution in 15,000 s. Figure 7 compares the CPU time of the HMCGP-UFGA with the exact method. From Fig. 7, by increasing the problem size, the CPU time of the MCGP-UF grows exponentially. However, the performance of the HMCGP-UFGA is reasonable in terms of CPU time. Figure 8 shows the gap of the solution obtained by the HMCGP-UFGA for each objective. The term $\frac{\text{Hybrid}_{sol} - \text{MCGP}-\text{UF}_{sol}}{\text{MCGP}-\text{UF}_{sol}} \times 100$ is applied to compute the gap where Hybrid_{sol} denotes the solution obtained by the hybrid method and $\text{MCGP}-\text{UF}_{sol}$ is the solution obtained by MCGP-UF. It should also be noted that for the MCGP-UF model, the weight of each objective
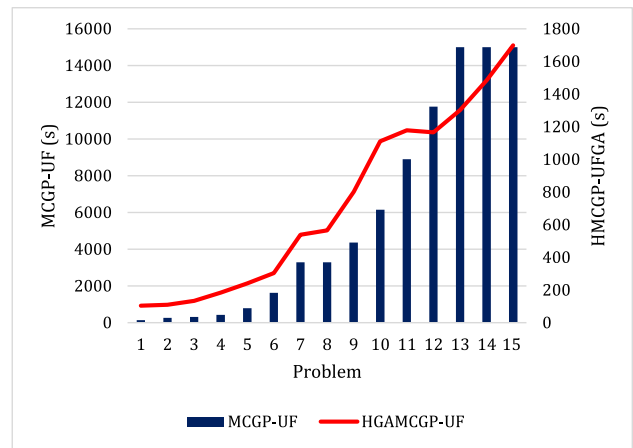

Fig. 7 CPU time of the HMCGP-UFGA against MCGP-UF for different problem sizes

function is considered $w_1 = 0.6$, $w_2 = 0.4$ according to expert opinions.

Based on the results, the average gap between the HMCGP-UFGA and MCGP-UF is 2.46%. The optimization gaps obtained for all instances show an admissible range (less than 5%) and the HMCGP-UFGA reduces the solution time by at least 8% in comparison with the MCGP-UF, bringing up that the former outperforms when used for large-scale problems. This indicates the good performance of the proposed algorithm.

Also, for this case study, four major products, namely milk, yogurt, cheese, and butter, are considered. On the other hand, the number of DCs, PCs, and retailers' outlets is shown in Fig. 9. Keep in mind that the demands and market sizes are almost the same for each location and its covered area.

Considering the weight of each objective function $w_1 = 0.6$, $w_2 = 0.4$, the value for the two objectives is calculated as 27,154,556,785.36 and 16253670.19. Obtained in the optimal solution, four DCs (Gorgan, Borujerd, Zahedan,

Table 4 Generate real data according to behavior KIDG data

Parameter	Corresponding random distribution	Parameter	Corresponding random distribution	Parameter	Corresponding random distribution
FC_{mt}	Uniform (550000, 2350000)	MD_{prt}	Uniform (2000, 148000)	RCF_{vdrt}	Uniform (100, 650)
FC_{dt}	Uniform (400000, 1500000)	CP_m	Uniform (5000, 150000)	RE_{mt}	Uniform (1000, 6000)
FC_{dmt}	Uniform (10000, 96000)	CD_d	Uniform (1000, 180000)	RE_{dt}	Uniform (800, 5500)
FC_{rdt}	Uniform (9500, 85450)	C_v	Uniform (5000, 100000)	RE_{pdt}	Uniform (300, 3000)
SC_{mdt}	Uniform (1500, 7500)	PE_{rt}	Uniform (0, 0.5)	RE_{pmdvt}	Uniform (750, 8000)
SC_{drt}	Uniform (2700, 50000)	STL_{rvt}	Uniform (50, 150)	RE_{pdrvt}	Uniform (750, 15000)
CHI_{dt}	Uniform (150, 980)	STE_{rvt}	Uniform (30, 120)	RE_{vrt}	Uniform (500, 2500)
PC_{pmt}	Uniform (105, 780)	LST_{rvt}	Uniform (20, 100)	RE_{pmt}	Uniform (1500, 7000)
CF_{vt}	Uniform (100, 850)	EST_{rvt}	Uniform (150, 350)	LF_p	Uniform (1, 5)
MS_{drvt}	Uniform (20, 650)	Ds_{dr}	Uniform (20, 850)	M	10000000

Table 5 Comparison between MCGP-UF and HMCGP-UFGA

No	Problem size						MCGP-UF			HMCGP-UFGA				
	R	D	M	P	T	V	Minimization total cost	Minimization CO_2 emission	CPU time	Minimization total cost	GP1%	Minimization CO_2 emission	GP2%	CPU time
1	3	1	1	2	3	2	82,540,047.24	10324.14	141	82,540,047.24	0.0	10324.14	0.0	104
2	4	2	1	2	2	3	87,056,879.67	11047.23	264	87,056,879.67	0.0	11047.23	0.0	110
3	5	3	1	3	3	2	108,220,168.15	13501.47	311	108,220,168.15	0.0	13501.47	0.0	133
4	6	4	1	3	2	3	115,483,409.36	18733.07	427	116,011,005.12	0.5	18869.27	0.7	184
5	7	5	2	4	3	4	127,748,411.08	24687.21	785	128,795,503.16	0.8	24966.56	1.1	241
6	8	6	2	4	2	4	155,137,551.19	33258.39	1626	156,946,577.09	1.2	34155.16	2.7	304
7	9	7	2	5	4	3	176,081,608.45	45620.12	3290	177,269,815.43	0.7	45936.49	0.7	539
8	10	8	2	5	2	5	183,720,118.37	61472.05	3290	187,798,569.11	2.2	63830.74	3.8	565
9	12	10	3	6	4	5	185,987,510.68	75388.19	4360	191,698,789.18	3.1	78522.81	4.2	801
10	14	10	3	6	3	6	2,014,768,433.55	891057.2	6149	2,069,801,305.23	2.7	912102.33	2.4	1110
11	16	12	3	5	5	6	11,047,220,630.15	1053242.68	8900	11,485,015,880.38	4.0	1094592.14	3.9	1178
12	18	14	4	4	4	8	21,014,357,453.28	1238977.51	11758	21,931,770,635.66	4.4	1294698.28	4.5	1166
13	20	16	8	4	6	8	-	-	15000	25,203,023,571.41	-	1515981.23	-	1302
14	22	18	8	5	6	10	-	-	15000	30,220,867,109.08	-	1865934.96	-	1484
15	25	20	8	8	6	10	-	-	15000	38,589,467,498.15	-	2587107.65	-	1698

Fig. 8 Gaps in objective functions values obtained from the HMCGP-UFGA and MCGP-UF for different problem sizes
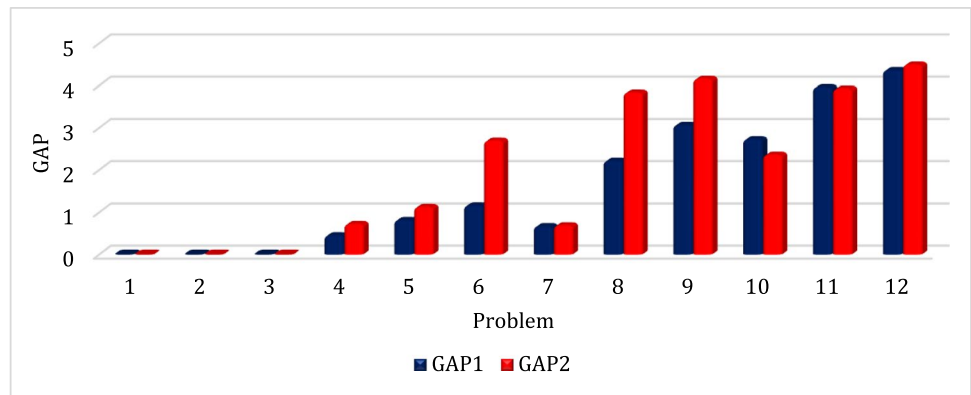
and Kerman) and two PCs (Hamedan and South Khorasan) have been opened (see Fig. 10).

According to the proposed algorithm, the optimal route considering the traffic is in Fig. 11. We have shown the optimal route for a candidate DC (Borujerd) in periods T1 and T2 (under traffic) (Fig. 11b), and periods T3 and T4 (without traffic) (Fig. 11a). The numbers in Fig. 11 indicate the amount of product delivered by different types of vehicles. Figure 11b indicates an alternative route and that by adding a vehicle, the amount of product delivered to retailers has a larger share than the traffic-free mode. For example, according to this figure, in period 1 (T1), the light truck has transferred 45368-unit milk, 2451-unit yogurt, and 91345-unit butter.

As mentioned earlier, dynamic pricing and demand management strategies along with dynamic transportation are considered to deal with perishable food supply chain disruption. Based on this, the pricing system is examined in different modes. In the first mode, the selling price of products is fixed and the demand depends on the price of the product. In the second mode, the selling price of the products varies according to the traffic conditions. Finally, in the third mode, the selling price of the products, besides the traffic conditions, also depends on the product's longevity and expiration date of the product. According to Table 6, as you can see in the no-traffic mode, the adoption of dynamic pricing (the third mode) has resulted in an approximate 13% and 8% improvement for the objective functions of total cost and CO_2 emission, compared to the first modes. But in traffic conditions, the adoption of dynamic pricing (the third mode) results in 27% and 18% improvement in the total cost and CO_2 emission respectively.

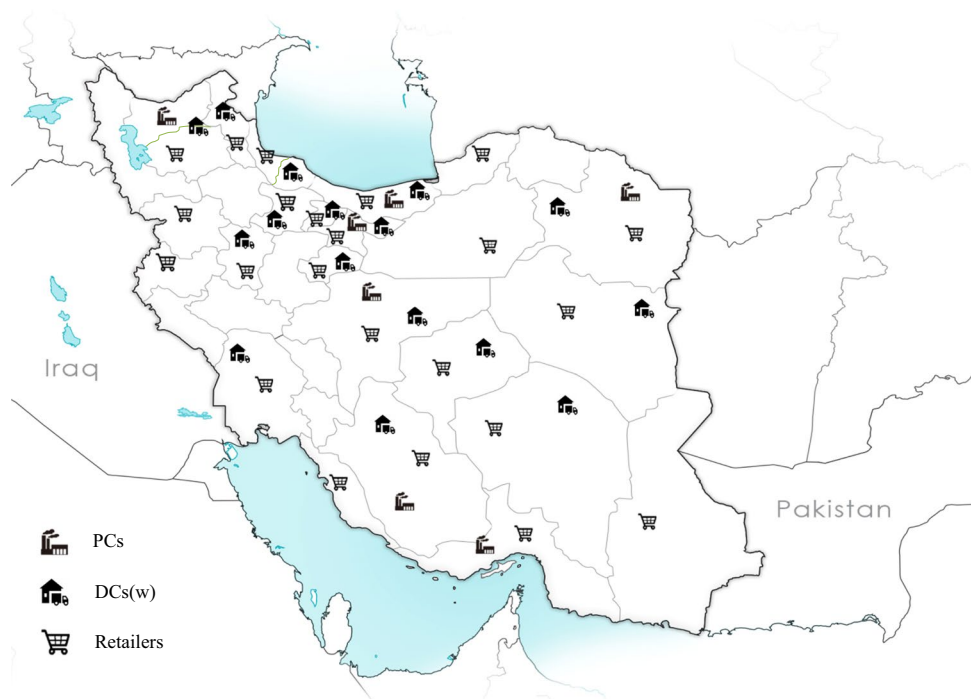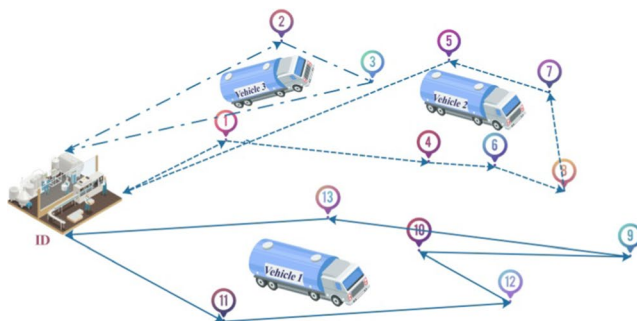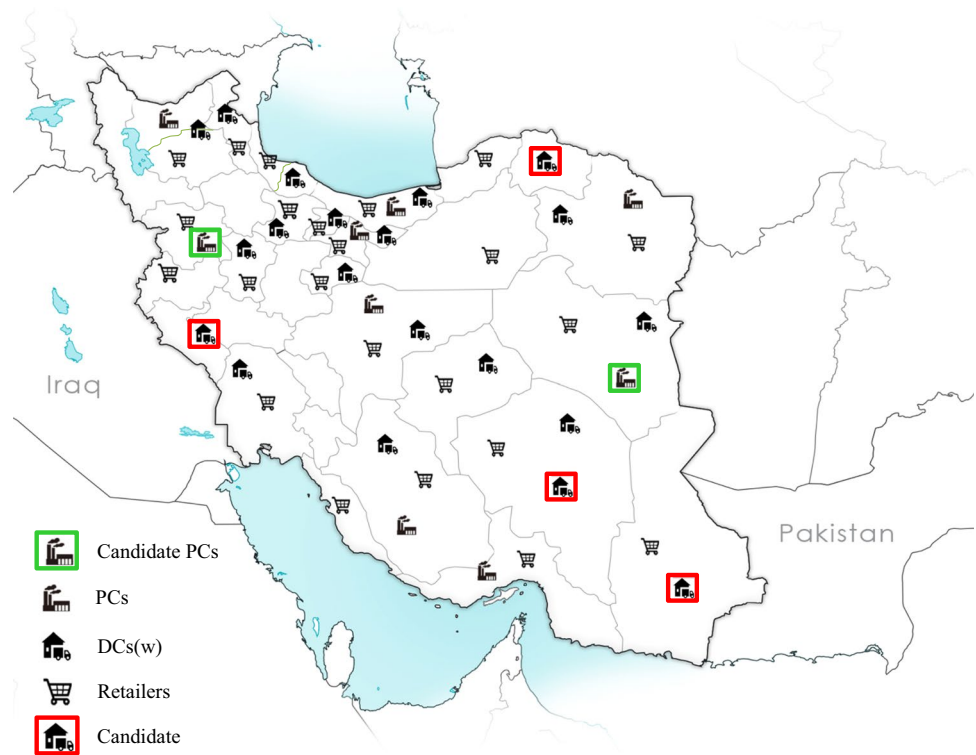**Fig. 9** Locations of different facilities of KIDG

Fig. 10 Locations of candidate DCs and PCs of KIDG

(b) with considering traffice condition

1 vehicle's trip =ID-11-12-10-9-8-13-ID

2 vehicle's trip =ID-1-4-6-7-5-ID

3 vehicle's trip =ID-2-3-ID

Optimal flow of products

period	T1			T2	
Vehicle Type / Product	heavy pickup	light truck	heavy truck	heavy pickup	light truck
milk	87321	45368	-	78245	-
yogurt	32142	2451	14735	-	45856
cheese	5515	-	102125	-	123400
butter	66314	91345	-	91454	-
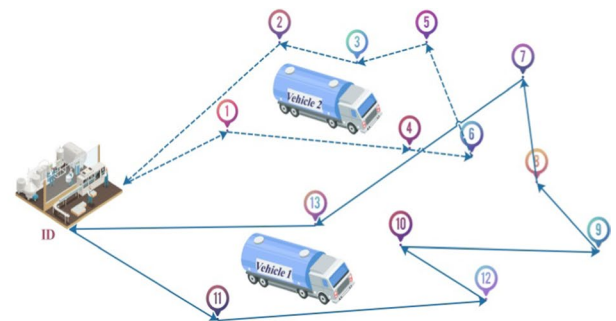
(a) without considering traffice condition

1 vehicle's trip =ID-11-12-10-9-8-7-13-ID

2 vehicle's trip =ID-1-4-6-5-3-2-ID

Optimal flow of products

period	T3			T4	
Vehicle Type / Product	heavy pickup	light truck	heavy truck	heavy pickup	light truck
milk	75314	32147	-	21435	9754
yogurt	15247	-	-	6471	10110
cheese	-	62140	-	18951	2147
butter	23451	8957	-	4786	10102

Fig. 11 Optimal routes for transferring products

Table 6 Comparison of different pricing strategies on objectives objective functions

Pricing strategies	Scenario	Minimization Total cost	Mean total cost	Standard deviation	Minimization CO_2 emission	Mean CO_2 emission	Standard deviation
Mode 1	Without traffic	28,481,789,407.03	27,391,113,288.13	6,529,588,853.30	17,140,855.62	16,707,285.76	3,699,709.07
	With traffic	34,486,287,117.41			19,179,330.82		
Mode 2	Without traffic	28,985,891,874.41	28,806,871,557.38	6,928,778,353.86	17,458,278.87	17,002,834.23	3,982,740.89
	With traffic	35,029,378,253.11			19,504,404.23		
Mode 3	Without traffic	25,205,123,369.05	26,179,840,077.21	5,696,567,436.69	15,871,162.61	14,938,047.25	3,592,976.70
	With traffic	27,154,556,785.36			16,253,670.19		

Sensitivity analysis

Here, the effect of some important parameters of the proposed model on the solution is investigated. Thus, the problem is solved with various values for the related parameters and the results are analyzed.

The effect of price elasticity on the problem

This section is devoted to investigating the effect of price elasticity on different pricing strategies. To do this, we solve the problem for different values of the price elasticity (-20%, -10%, -5%, $+5\%$, $+10\%$, and $+20\%$). The results of sensitivity analysis are exhibited in Tables 7 and 8. According to the results obtained in Tables 7 and 8, the pricing strategy in modes 1 and 3, when the PE_{rt} values are respectively smaller or greater than the values $PE_{rt} = 0.095, 0.110, 0.087, 0.090, 0.105,$ and 0.125 , improves the objectives of the problem. As shown in Tables 7 and 8, if the other problem parameters are constant and the PE_{rt} changes, for markets that are more sensitive to higher prices, it shows the increasing trend of cost and the environmental effects in mode 3 under disruption. On the other hand, by reducing the value of the PE_{rt}, mode 3 will improve the objective functions. As a result, by choosing a mode 3 pricing policy for markets with PE_{rt} changes of -5%, it will have a 21% improvement in cost performance and a 15 improvement in environmental performance compared to mode 1, while the choice of the pricing policy of mode 3 for markets with PE_{rt} changes of $+5\%$ has approximately 21% improvement in cost performance and 15% for the improvement of environmental performance compared to mode 1.

The impact of product longevity on objective functions

This section is exploring the effect of product longevity on the solution. Thus, the problem is solved for various values of the mentioned parameters. The results of sensitivity analysis are exhibited in Figs. 12 and 13. As shown in Fig. 12, by increasing product longevity, the total cost and the environmental impacts are decreased, too. Also, based on the obtained results, adopting the third mode policy leads to reducing the total costs of the logistics system compared with the other pricing strategies for different values of the lifetime parameter. On the other side, Fig. 13 shows that increasing the shelf-time results in decreasing the CO_2 emissions. It should be noted that in terms of environmental impact, again the third mode strategy has fewer emissions.

The impact of product demand on objective functions

Figure 14 exhibits the results of sensitivity analysis of the demand parameter. Based on this figure, increasing the demand parameter leads to increasing both objective functions. In this regard, a 30% decrease (increase) from the primary case results in a 20% (22%) decrease (increase) in the first objective function. Alternatively, a 30% decrease in demand leads to a 20% decrease in the second objective function while a 30% growth in demand leads to a 25% growth in the second objective function.

Table 7 The impact of price elasticity on the total cost objective ($)

Pricing policy		+20%	+10%	+5%	−5%	−10%	−20%
Mode 1	Without traffic	23905477894	25704814940	27057699937	28140007934	30391208569	33734241511
	With traffic	28945202935	31123874123	32761972762	34072451672	36798247806	40846055064
Mode 2	Without traffic	24328583697	26159767417	27536597281	28638061172	30929106066	34331307733
	With traffic	29401032902	31614013873	33277909340	34609025714	37377747771	41489300026
Mode 3	Without traffic	21155290172	22747623841	23944867201	24902661889	26894874840	29853311072
	With traffic	22791498374	24506987499	25796828946	26828702104	28974998272	32162248082

Table 8 The effect of price elasticity on the environmental impact objective (*t*)

Pricing policy		+20%	+10%	+5%	−5%	−10%	−20%
Mode 1	Without traffic	14386748.64	15469622.2	16283812.84	16935165.35	18289978.58	20301876.22
	With traffic	16097691.84	17309346.07	18220364.28	18949178.85	20465113.16	22716275.61
Mode 2	Without traffic	14653169.91	15756096.68	16585364.93	17248779.52	18628681.89	20677836.89
	With traffic	16370534.08	17602724.82	18529184.02	19270351.38	20811979.49	23101297.23
Mode 3	Without traffic	13321063.56	14323724.26	15077604.48	15680708.66	16935165.35	18798033.54
	With traffic	13642111.73	14668937.35	15440986.68	16058626.15	17343316.24	19251081.03

The impact of weights of the objective functions

This section is dedicated to investigating the effect of the weight of the objective functions on the solution. Thus, the problem is solved with different values for the weight of the objective functions, and the results are depicted in Table 9. Based on Table 9, when the weight of the first objective function is decreased from 0.8 to 0.2, the value of this function is increased by about 7.30%. However, by raising the weight of the second objective function from 0.2 to 0.8, the value of this function decreased about 13.53%. In general, based on Table 9, by increasing the weights of each objective function, the value of that function is improved.

Managerial implications

A manager's tasks include setting objectives, identifying a path to achieve them, and making strategic, tactical, and operational decisions. To keep this promise, it is critical to supply managerial insights, and in this section, we provide some of the useful insights from the proposed PFSCN.

- First of all, this research provides a benchmark model for PFSCN managers to successfully implement and manage LIR decisions under disruption and meanwhile address sustainable goals in the dairy industry. Many requirements of PFSCN problems were ignored or addressed partially in the literature, such as environmental, multi-product, multi-period, and multi-level effects. Theoretically, in this study, considering the resiliency aspects helps to determine the best strategies to cope with disruptions in a PFSCN. This study also directly addresses integrated approaches from several different perspectives by designing the PFSCN with pricing policies and LIR issues under disruption. To clarify, unlike other models, the impact of traffic conditions related to the time window has been considered to increase customer satisfaction in our study. Also, different pricing strategies have been discussed. According to the obtained results of the "Case study" section, the proposed approach helps PFSCN managers to make valuable decisions to manage demand under disruptions.
- According to the results of Tables 6 and 7, after examining the markets of their products, managers can achieve

Fig. 12 Sensitivity analysis of the first objective function over the longevity parameter
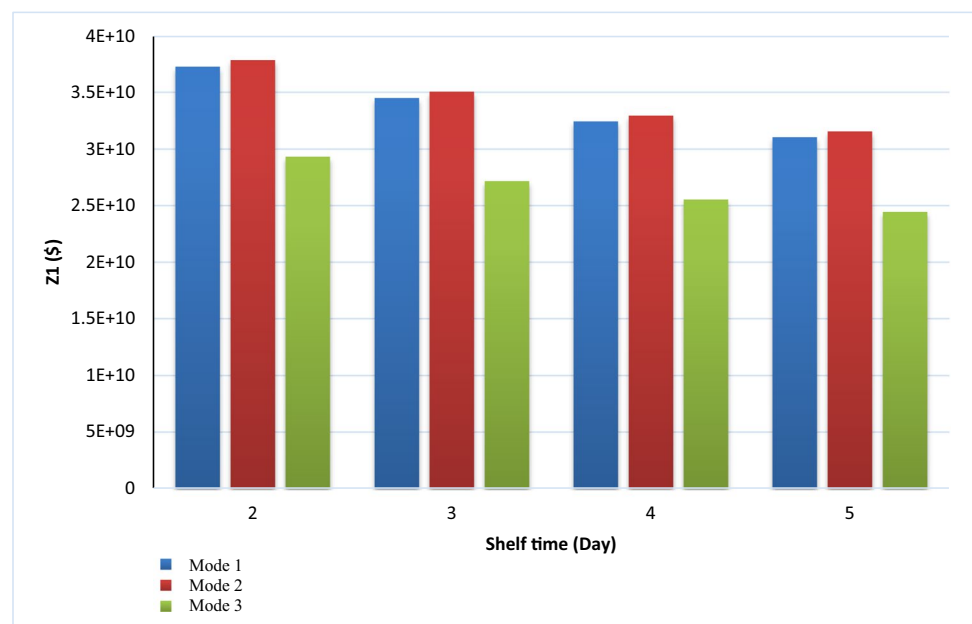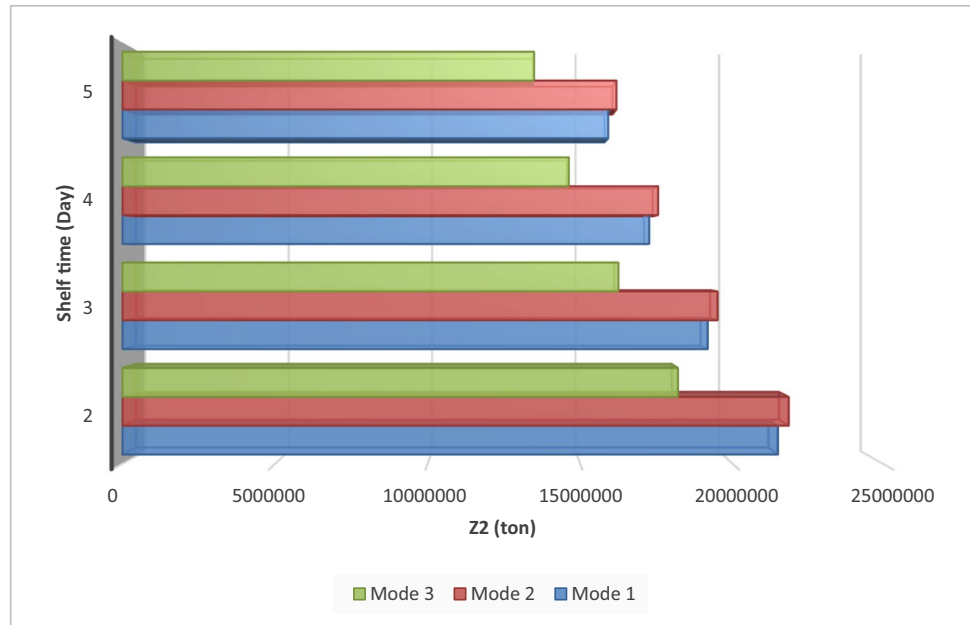
Fig. 13 Sensitivity analysis of the second objective function over the longevity parameter

the best policy to reduce costs. Thus, profitability can be increased by categorizing the market into less price elasticity and more price elasticity, to properly manage demands during disorder.

- As discussed in the theoretical section, the model's results favor the organization in two ways. Using a dynamic pricing policy, economic costs have decreased by 13%, and CO_2 emission has decreased by 8% without traffic conditions. Moreover, a dynamic pricing policy causes economic costs to decrease by 27% and CO_2 emis-

sions to decrease by 18% with traffic conditions. Nonetheless, considering Iran's developing economy, environmental responsibility may often be ignored, although it is a critical concern in the business world. Therefore, choosing a suitable pricing policy, sales planning process, and demand management can be a good lever for food supply chain resilience.

- According to Figs. 12 and 13, the pricing policy is shifted to periods with less probability of disruption in the event of potential disruptions to meet customer demand. This

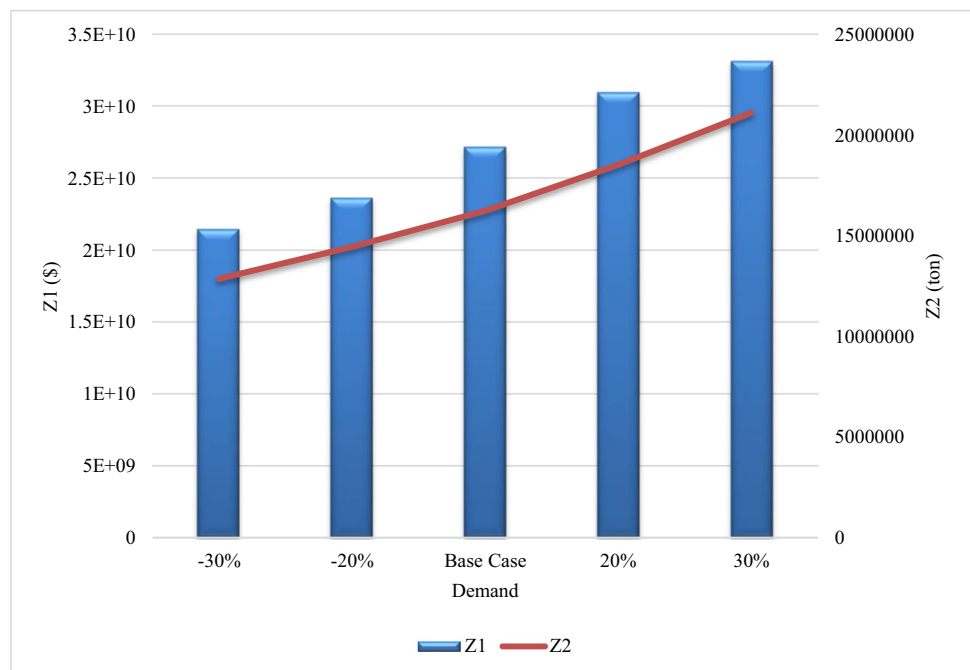**Fig. 14** Sensitivity analysis of the demand parameter

Table 9 The effect of changing the objective function's importance

Problem	w_1	w_2	Z_1	Percentage of change (Z_1)	Z_2	Percentage of change (Z_1)
1	1	0	27154556785	0.00%	17306908.02	0.00%
2	0.8	0.2	27154556785	0.00%	17306908.02	0.00%
3	0.6	0.4	28066949893	3.36%	16253670.19	−6.48%
4	0.5	0.5	29009999409	3.36%	16253670.19	−6.48%
5	0.4	0.6	30620054377	5.55%	14753456.43	−9.23%
6	0.2	0.8	32855318346	7.30%	12757313.78	−13.53%
7	0	1	35253756585	7.30%	12757313.78	−13.53%

is fine if the demands of subsequent courses are met at a lower price. As a result, inventory levels in DCs and retailers are limited by increasing product longevity. However, adopting a dynamic pricing policy reduces costs and carbon emissions by increasing product longevity expectancy. On the other hand, by reducing product longevity, more costs will be imposed on the chain. However, perishable and price dynamics have been sufficiently recorded. As a result, the inventory policy at the strategic level increases product longevity, causing manufacturers to compete fiercely in designing their PFSCN.

Conclusions

This study presented a multi-objective mixed-integer optimization formulation to design a perishable food supply chain for the LIR problem under disruption, which aimed to minimize the total cost and environmental impact in a real dairy industry case. According to the recent literature review, the issue of LIR in the design of supply chains for perishable food should be examined carefully. To the best of our knowledge, this article is among the first research work that addresses a multi-period, multi-product, multi-level, multi-objective LIR problem. Additionally, dynamic pricing and transportation are considered resilient strategies to reduce the effects of disruptions with related traffic conditions. On the other hand, several characteristics such as fuel consumption, traffic effects, different capacities for vehicles, and the speed of vehicles under traffic were considered to analyze environmental and economic impacts. Since the traffic-related time window was defined for DCs serving retailers, the level of satisfaction of retailers was also considered. A seldom-noticed characteristic, which is studied in this research, is the consideration of several planning periods and the introduction of dynamic pricing strategies taking into account product life and traffic disturbances in the calculations. Besides, a new HMCGP-UFGA algorithm is proposed to solve the LIR problem for the perishable food supply chain. Based on the results, the proposed method

HMCGP-UFGA has an efficient and effective effect on the quality of solution and solution time in large-size problems. On the other hand, the results of sensitivity analysis showed that the dynamic pricing strategy had a greater impact on the objectives of the problem than other strategies and can improve the objectives with or without traffic disruptions. Also, increasing the life of products, by, for example, efficient packaging, has reduced costs and environmental effects. However, it is worth to mentioning that the effect of a good dynamic pricing policy has been more than increasing the life of the product.

Limitations

The limitations of this research are summarized as follows:

1- It is assumed that all input parameters are deterministic and available. However, some parameters have some uncertainties, such as demand, in the real world.
2- The numerical results are attained by applying the proposed model to a case study of the dairy industry in Iran. More studies and practical implementations of the proposed model can lead to more solid results.
3- We use a heuristic approach to provide near-optimal solutions in a reasonable time. However, optimal solutions of the proposed model are more favorable than those provided by the heuristic approach; the existing commercial solvers have some technical limitations to solve the large-scale sample of this NP-complete problem in a reasonable time.

Directions for future research

Given the limitations of this research, researchers can expand this research in several ways. Since the situation in the real world is always accompanied by uncertainty, this study can be made more realistic under the uncertainties in the data of real-world problems. On the other hand, using approaches in this study to design a closed-loop food supply chain can more comprehensively examine the environmental

and cost effects. Additionally, one of the intriguing subjects for future research might be a full comparison of the performance of the proposed HMCGP-UFGA with other algorithms in the literature on solution time and solution quality.

Declarations

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