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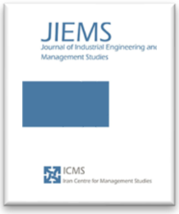

Designing a Perishable Food Supply Chain Model and Analyzing the Financial Risk of Purchase and Distribution

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Abstract

Perishable food supply chains (PFSCs), particularly in the dairy sector, face significant challenges due to product deterioration, quality degradation, and financial risks associated with distribution delays. Despite extensive research on supply chain optimization, a critical gap remains in accurately modeling the dynamic relationship between product shelf-life and selling price—a factor that significantly impacts revenue and risk assessment in real-world operations. This study addresses this gap by developing a multi-objective optimization model for the dairy supply chain in Iran that incorporates: (1) a novel stepwise pricing mechanism based on remaining shelf-life, capturing revenue loss due to spoilage; (2) financial risk assessment of purchase and distribution operations; (3) transportation planning with vehicle routing; and (4) discount sales policies aligned with product freshness. Given the NP-Hard nature of the problem, NSGA-II and MOPSO algorithms with a modified priority-based encoding-decoding method were employed. Algorithm parameters were systematically tuned using the Taguchi method. The model was validated through a numerical example solved via the LP-metric method, followed by 15 larger test problems to evaluate algorithm performance. Comparative analysis using multiple evaluation metrics—including the number of Pareto-efficient solutions (NPF), maximum spread index (MSI), spacing metric (SM), and computational time—was conducted. The TOPSIS technique was applied to rank algorithm performance, revealing that NSGA-II (weight = 0.6945) significantly outperforms MOPSO (weight = 0.3055) across all problem sizes. The key contributions of this research include: (i) introducing a realistic stepwise pricing function linked to perishability, (ii) integrating financial risk into PFSC optimization, and (iii) providing a robust algorithmic framework for large-scale dairy supply chain problems. These findings offer practical guidance for managers seeking cost-effective, risk-aware, and quality-conscious management of perishable food supply chains.

Keywords: perishable food supply chain ,multi-objective optimization, stepwise pricing, financial risk, NSGA-II; MOPSO, dairy products.

Paper Type: Original Research

1. Introduction

Nowadays, companies are forced to design and manage supply chains better due to the competitiveness of markets and the development of management concepts (Govindan et al., 2020). Supply Chain Management (SCM) emphasizes the integration of chain members because it is not possible to consider the decisions of a supply chain separately and optimize it to increase its efficiency (Sahebjamnia et al., 2018). People's demand for food has increased dramatically recently due to rapid population growth. This is why the food industry is one of the most important industries. Food supply chain management (FSCM) plays a very important role in managing the high demand for food (Chernonog, 2020). Accordingly, the preparation, production, maintenance, and storage of goods, inventory control, distribution, delivery, and customer service, which were previously done at the company level, have now been transferred to the supply chain level (Jouzdani & Govindan, 2020). So, SCM has become more important in the food industry. On the other hand, logistics and transportation in the supply chain need special planning due to the amount of pollution (Biuki et al., 2020). Closed-loop supply chains can enhance efficiency, sustainability, and waste reduction for perishable products by recovering waste or packaging and utilizing reverse logistics (Zarreh et al., 2024). The supply chain of perishable foods requires a life cycle perspective, as energy consumption, waste, and environmental impacts are significant across all stages of production, packaging, transportation, storage, and distribution (Toniolo et al., 2024). It is necessary to make strategic and tactical decisions about the location

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and allocation of relevant facilities in the network, as well as the optimal transfer and maintenance of the product so that an FSCN is effective (Arab et al., 2020). Sustainability and resilience must be considered in dairy supply chain planning, the selection of suppliers, processing/distribution centers, transportation mode, and product transfer methods should be guided by environmental criteria and the ability to withstand changes (Zarei-Kordshouli et al., 2023). Perishable products need special measures because they have social and environmental effects in addition to their known economic aspects (Yavari et al., 2020). Dairy products are perishable products that require special planning. Perishable products, such as dairy, require special measures in logistics, transportation, storage, and distribution, as they are highly sensitive to quality, shelf life, storage conditions, and waste. Therefore, strategic and tactical decisions regarding the location and allocation of facilities, product transfer and storage, and transportation routes are critically important for an effective perishable food supply chain network (FSCN) (Moreno-Camacho et al., 2023). Dairy products are important sources of nutrition for many people around the world. There is a growing global demand for dairy products. Dairy production has quadrupled over the past 50 years. More than 320 million tons of dairy products are produced annually in the world (Mohebalizadehgashti et al., 2020). However, dairy production has many negative environmental consequences, such as increased greenhouse gas emissions, destruction of agricultural land, and increased use of fresh water. One of the most important challenges in the world is reducing the negative environmental consequences of the production and consumption of dairy products and other protein products. The global production of dairy products has increased rapidly during the last 50 years. According to Figure 1, dairy production has more than doubled since 1961. Global dairy consumption per capita can be seen in Figure 1.

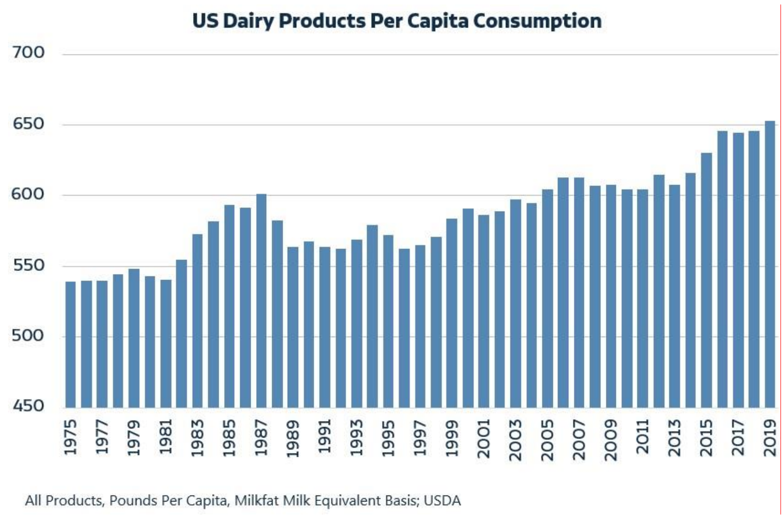

Figure 1. Dairy products consumption trend

Organizations pay more and more attention to the necessity of using systems that can perform distribution and transportation operations as efficiently as possible due to the development of dairy product production in Iran. Furthermore, transportation planning is extremely important to reduce energy consumption, costs, pollution, and social costs due to the reduction of fuel reserves in the world and the increasing need to optimize energy consumption in all organizations. In addition to the above, global warming in recent years has caused environmental protection organizations to pass laws to reduce carbon emissions. So, the reduction of fossil fuel consumption should be considered a basic objective and should be given more attention than other objectives, such as minimizing the total transportation time (logistics time) and the distance traveled in all industries, especially transportation planning. The multidimensional challenge of perishable foods, environmental problems, and the importance of material and information flow in the supply chain have led to the development of SCM at the operational level. The increase in requirements has led to the integration of horizontal and vertical supply chains, market segmentation, increasing the provision of differentiated or different products, and the dominance of multinational companies in food processing and the sales and marketing departments of companies (Khalafi et al., 2020). Recent studies have further advanced the integration of vehicle routing, sustainability, and coordination mechanisms in supply chain optimization .Ayough et al. (2020) addressed the three-dimensional capacitated vehicle routing problem (3L-CVRP) with time windows, proposing a hybrid simulated annealing algorithm to minimize transportation costs while considering both vehicle capacity and loading constraints—a critical aspect often overlooked in traditional routing models. In the context of closed-loop supply chains, Khorshidvand et al. (2021a) developed a two-stage model that integrates pricing, green quality, and advertising decisions with sustainable objectives, demonstrating that coordination tools significantly enhance economic, environmental, and social performance. Extending this work, Khorshidvand et al. (2021b) proposed a hybrid approach incorporating robust optimization to handle demand uncertainty, showing that simultaneous consideration of pricing, greening, and advertising improves both profit and emission reduction outcomes. Furthermore, Khorshidvand et al. (2021c) presented a sustainable closed-loop supply chain model using Lagrangian relaxation, achieving near-optimal solutions with significantly reduced computational time for large-scale instances. These studies highlight the growing importance of integrating coordination decisions with network design under uncertainty, an approach that aligns with the multi-objective framework adopted in the present study. Therefore, this study aims to plan the distribution supply chain for a dairy products manufacturing company in Iran. Since dairy products are among the most important products, the accurate evaluation of the optimal solutions of the supply chain is very important because the inappropriate evaluation of the space of Pareto optimal solutions of the problem brings irreparable losses to the operational field of the supply chain. Considering the objectives of this study, the proposed innovations include planning the distribution supply chain in the dairy products industry, with the goal of optimizing distribution costs. A critical characteristic of perishable food supply chains is the strong dependency of product quality and market value on remaining shelf-life. However, a review of existing literature indicates that most prior studies either oversimplify or entirely ignore the dynamic nature of selling prices as products deteriorate. In this study, the selling price is modeled as a **stepwise function of product perishability**, directly linked to the remaining shelf-life. This feature allows the model to accurately represent real market behavior—especially in dairy supply chains—and enables better evaluation of financial risks associated with delays, suboptimal routing, or quality degradation. This pricing mechanism represents one of the **key innovations** of the proposed research, significantly enhancing the realism and practical relevance of the model. The use of efficient novel meta-heuristic algorithms is of great importance considering the evaluation space of the studied problem, which is NP-Hard HARD (Schneider, 2017; Fathollahi-Fard & Hajiaghaei-Keshteli, 2018; Hajiaghaei-Keshteli & Fathollahi-Fard, 2019; Samadi et al., 2018). A systematic review of optimization studies in the dairy supply chain in Table 1 shows that the use of mathematical models and, gradually, artificial intelligence and machine learning algorithms is expanding in this industry (Malik et al., 2022). So, the simultaneous use of NSGA-II and MOPSO algorithms in evaluating the Pareto front of optimal solutions in the supply chain of dairy products was discussed.

Table 1. Literature review

Year	Authors	Article Title	Problem Type / Topic	Model Objectives	Decision Variables	Model Parameters	Solution Method / Algorithm
2020	Govindan et al.	Social sustainability tensions in multi-tier supply chains	SCM	Analyze social sustainability tensions	Social factors	Sustainability indicators	Conceptual analysis
2018	Sahebjamnia et al.	Sustainable closed-loop supply chain network design	SCM	Improve overall supply chain efficiency	Facility location, capacities, material flow	Costs, environmental impacts, job opportunities, work hazards	MILP
2020	Chernonog	Inventory and marketing policy in a supply chain of a perishable product	FSCM	Investigate the effect of power structure (leader/follower) on pricing, advertising, cycle length, and profit	Material flow	Demand parameters, advertising cost, product perishability, shelf-life effect on demand	Conceptual modeling
2020	Jouzdani & Govindan	Sustainable perishable food supply chain network design	FSCM	Optimize total cost, energy consumption, and traffic congestion	Resource allocation	Social, environmental, and economic aspects	Multi-objective mathematical programming + Goal Programming
2020	Biuki et al.	Integrated location, routing, and inventory management model for sustainable perishable supply chains	SCM	Reduce pollution	Route and vehicles	Costs and emissions	MILP
2024	Zarreh et al.	Closed-loop supply chain for perishable products	FSCM	Reduce waste	Returned quantities	Recycling rates	Systematic review + method and findings analysis
2024	Toniolo et al.	Integration of product life cycle perspectives in fresh food supply chains: intra- and inter-organizational review	FSCN	Reduce energy consumption and waste	Level of adoption of practices and waste-reducing actions by each supply chain actor; technology implementation	Energy consumption, production waste, packaging characteristics, product lifetime, carbon emission, seasonal and	Systematic literature review + multi-dimensional analysis of life cycle aspects; categorization and evaluation

						supply chain parameters	
2020	Arab et al.	Bi-objective inventory-routing problem with returns under transportation risk	VRP	Minimize total system cost and risk-based transportation	Inventory levels, delivery schedule	Vehicle capacities, start-up, distribution, and maintenance costs	Multi-objective Imperialist Competitive Algorithm (MOICA) + NSGA-II
2023	Zarei Kordshouli et al.	Dairy supply chain network design with sustainability and resiliency approach	SCM	Minimize total supply chain costs	Routes, supplier selection, regional demand	Supplier ranking using MADM	Preemptive Fuzzy Goal Programming
2020	Yavari et al.	Location-routing of perishable products under disruptions	VRP	Maximize total supply chain profit with resilient strategy	Facility location, inventory levels, routing plan, dynamic/disruptive pricing	Product lifetime, price elasticity, route disruption	Genetic Algorithm (GA)
2023	Moreno Camacho et al.	Sustainable supply chain network design: A case study in Colombian dairy sector	SCM	Maintain quality and distribution	Routes, allocation	Quality and shelf-life	MILP
2019 2018	Fathollahi-Fard & Hajiaghaei-Keshteli	Stochastic multi-objective model for closed-loop supply chain design with environmental considerations	VRP	Reduce cost and time	Route, allocation	Distance, capacity	NSGA-II, MOPSO
2022	Malik et al.	Application of optimization techniques in dairy supply chains: A systematic review	SC	Smart optimization	-	-	Review study
2020	.Ayough et al	An integrated approach for 3D capacitated vehicle routing problem considering time windows	VRP	Minimize total transportation costs	Vehicle routes, loading sequence	Vehicle capacity, time windows, 3D loading constraints	Hybrid SA algorithm
2021	Khorshidvand .et al	Developing a two-stage model for a sustainable CLSC with pricing and advertising decisions	CLSC	Maximize profit, minimize CO_2, improve social impacts	Price, greenness, advertising, facility location, inventory	Demand elasticity, emission rates, social factors	Augmented ε-constraint, Lagrangian relaxation
2021	Khorshidvand .et al	A hybrid modeling approach for green and sustainable CLSC considering price, advertisement and uncertain demands	CLSC	Maximize profit, minimize CO_2 emission	Price, greenness, advertising, facility location	Uncertain demand, return rate sensitivity, green quality tolerance	Robust optimization, Lagrangian relaxation
2021	Khorshidvand .et al	Sustainable closed-loop supply chain network: Mathematical modeling and Lagrangian relaxation	SCLSC	Maximize profit, minimize CO_2, maximize employee safety	Price, green quality, advertising, allocation	Demand sensitivity, emission factors, workplace safety	MOMILP, Lagrangian relaxation

2. Problem Definition / Modeling

In the proposed model, one of the core components is the explicit incorporation of product perishability and its direct impact on selling price. Unlike traditional models that assume a constant or linear price, this study defines the selling price as a stepwise function based on remaining shelf-life. As freshness decreases and the product approaches its expiration date, the selling price transitions through several predefined discount levels. This stepwise pricing mechanism accurately captures the economic impact of deterioration and enables a more precise assessment of financial risks associated with delays, inventory accumulation, or quality loss. This feature differentiates the proposed model from previous studies and represents one of its primary methodological innovations. Therefore, the study sought to provide a mathematical model of distribution planning in the supply chain. Therefore, the problems such as financial risks in purchase and distribution, transportation for supply and distribution of products, discount sales policies, and maintaining manufactured products in the PFSC should be addressed in the new supply chain discussions. In this section, a direct supply chain model aligned with the operational policies of manufacturing companies will be evaluated and analyzed as a four-level supply chain problem (as shown in Figure 2).

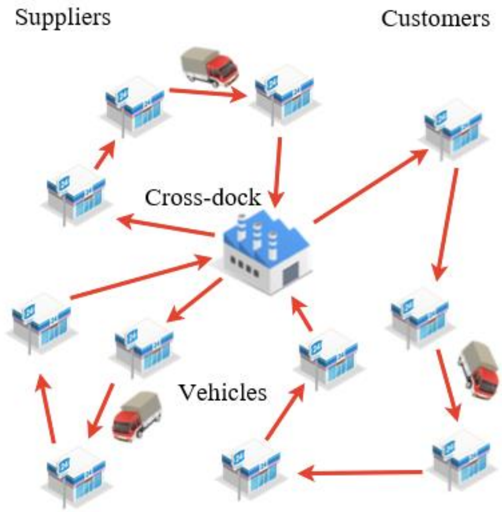

Figure 2. A 4-level direct supply chain model

2.1. The Assumptions

The main assumptions of the proposed model are as follow:

- The studied supply chain has 4 levels including supplier, cross-dock, distributor, and final customer;
- This supply chain is multi-product and multi-period;
- Customer demand has uncertainty and robustness;
- Vehicles are homogenous;
- Vehicles have limited capacity;
- The number of vehicles is limited;
- The products under review are perishable;
- The selling price is a function of the product perishability;
- Products are delivered to customers in a hard-time window;

2.2. Indices and Sets

S: The set of suppliers where S = {1,2, …, Ns}

C: The set of customers as C = {1,2, …, N}

P: The set of perishable products as P = {1,2, …, NP}

K: The set of inbound vehicles as K = {1,2, …, NK}

K': The set of outbound vehicles as K' = {1,2, …, NK'}

DIN: The set of cross-dock entrance doors as DIN = {1,2, …, NDIN}

DOUT: The set of cross-dock exit doors as DOUT = {1,2, …, NDOUT}

t: The set of time windows as TW = {1,2, …, NTW}

Op: The set of the number of price reduction points where Op = {1,2, …, Op}

2.3. Model Parameters

D_{cpt}: The demand for product p by customer cat time t

CV_k: The fixed costs of using vehicle k (including driver's salary, insurance, etc.)

rsk_k: the risk of using vehicle k due to wear and tear (probability of vehicle k breaking down in one day)

C_k: the cost of transporting vehicle type k per unit of distance traveled

tC_s: The fixed cost of loading from supplier s

ai: The break-even point of the price of product p (time unit)

α: The time factor of unloading a product unit (product weight) in the cross-dock

α': The time factor of loading a product unit (product weight) in the cross-dock

TC_{ks}: The cost of transporting vehicle k from the cross-dock to supplier s

$price_{pst}$: the cost of purchasing each unit of product p from supplier s at time t

D_s: The distance between the cross-dock and the supplier

$D_{ss'}$: The distance between supplier s and s'

Dis_c: The distance between the cross-dock and the customer

$Dis_{cc'}$: The distance between customer c and c'

$FC_{d_{in}t}$: The fixed cost of establishing the entrance door of cross-dock d_{in} at time t

VP_p: The volume factor of each product p

V: The capacity of the cross-dock

VV_k: The capacity of vehicle k

SS_p: The cost of sorting each unit of product p in the cross-dock

B_p: the fractional cost of each unit of product p of the cross-dock

p_e: The penalty of one unit of service tardiness

p_k: The penalty of one unit of service lateness

pr_p: the selling price of product p to customers

¥ γ: Sales price adjustment factor based on sales time window

U: A very large number

A: Step Function

$$Pr_p(t) = \begin{cases} P_1 & if \quad t<a_1 \\ P_2 & if \ a_1 \le t < a_2 \\ P_3 & if \ a_2 \le t < a_3 \\ P_{op} & if \ t \ge a_{op} \end{cases}$$

Prp (t) =	P1	t<a1
	P2	a1 ≤t< a2
	P3	a2 ≤t< a3
	Pop	t ≥aop

B: Descending Function

$$Pr_p(t) = \begin{cases} p & if \quad t = 0 \\ \dfrac{t-p}{a_{op}} & if \ a_2 \le t < a_3 \\ o & if \ t = a_{op} \end{cases}$$

Prp (t) =	P	t=0
	$\frac{t-p}{a_{op}}$	a2 ≤t< a3
	o	t =aop

2.4. Variables

$Q_{pks\mathrm{d}_{in}t}$: The quantity of product p delivered from supplier s to the entrance door of cross-dock d_{in} by inbound vehicle k at time t

$QP_{pk'\mathrm{d}_{out}ct}$: The quantity of product p delivered from supplier s to the exit door of cross-dock d_{out} by outbound vehicle k′ at time t

QQ_{pkss_1t}: The quantity of product p delivered from supplier s1 to supplier s by outbound vehicle k at time t

$QPT_{pk'\mathrm{d}_{out}cc_1t}$: The quantity of product p delivered from supplier c to supplier c1 by outbound vehicle k′ at time t

$sl_{\mathrm{d}_{out}pt}$: The quantity of product p in cross-dock d_{out} at time t

$X_{k\mathrm{d}_{in}st}$: It is a paired variable that will be 1 if vehicle k moves from cross-dock d_{in} to supplier s at time t and 0 otherwise

XX_{kss_1t}: It is a paired variable that will be 1 if vehicle k moves from supplier s1 to supplier s at time t and 0 otherwise

$XXX_{ks\mathrm{d}_{in}t}$: It is a paired variable that will be 1 if vehicle k moves from supplier s to cross-dock d_{in} at time t and 0 otherwise

$Y_{k'\mathrm{d}_{out}ct}$: It is a paired variable that will be 1 if vehicle k′ moves from cross-dock d_{out} to customer c at time t and 0 otherwise

$YY_{k'\mathrm{d}_{out}cc_1t}$: It is a paired variable that will be 1 if vehicle k′ moves from customer c to customer c1 at time t and 0 otherwise

$YYY_{k'c\mathrm{d}_{out}t}$: It is a paired variable that will be 1 if vehicle k′ moves from customer c to cross-dock d_{out} at time t and 0 otherwise

$bX_{d_{in}t}$: It is a paired variable that is 1 if the entrance doors of cross-dock d_{in} are established at time t and 0 otherwise

$bX_{d_{out}t}$: It is a paired variable that is 1 if the entrance doors of cross-dock d_{out} are established at time t and 0 otherwise

ye_c: The service earliness to node c

Yl_c: The service tardiness to node c

2.5. Mathematical Model

$$
\begin{aligned}
\mathrm{MAX}\,Z1 = {} & \sum_{p}\sum_{k,k'}\sum_{\mathrm{d}_{out}}\sum_{c}\sum_{c1}\sum_{t}(QP_{pk'\mathrm{d}_{out}ct} + QPT_{pk'\mathrm{d}_{out}cc_1t}) * ¥ * \mathrm{pr}_p \\
& - \Bigg(\sum_{p}\sum_{k}\sum_{s}\sum_{\mathrm{d}_{in}}\sum_{t}\sum_{s1\neq s}(Q_{pks\mathrm{d}_{in}t} + QQ_{pkss_1t}) * price_{pst} + \sum_{p}\sum_{k'}\sum_{\mathrm{d}_{out}}\sum_{c}\sum_{c1}\sum_{t}(QP_{pk'\mathrm{d}_{out}ct} + QPT_{pk'\mathrm{d}_{out}cc_1t}\Bigg) \\
& * SS_p + \sum_{p}\sum_{k}\sum_{s}\sum_{\mathrm{d}_{in}}\sum_{t} Q_{pks\mathrm{d}_{in}t} * C_k * D_s + \sum_{k'}\sum_{p}\sum_{\mathrm{d}_{out}}\sum_{c}\sum_{t} QP_{pk'\mathrm{d}_{out}ct} * C_k * Dis_c \\
& + \sum_{p}\sum_{k}\sum_{s}\sum\nolimits_{s1}\sum_{t} QQ_{pkss_1t} * C_k * D_{ss'} \\
& + \sum_{p}\sum_{k}\sum_{c}\sum\nolimits_{c_1}\sum_{t}\sum_{\mathrm{d}_{out}} QPT_{pk'\mathrm{d}_{out}cc_1t} * C_k * Dis_{cc'} + \sum_{k,k'}\sum_{\mathrm{d}_{out}}\sum_{c}\sum\nolimits_{s}\sum_{t} CV_k * (X_{k\mathrm{d}_{in}st} + Y_{k'\mathrm{d}_{out}ct}) \\
& + \sum_{\mathrm{d}_{in}}\sum_{t} BX_{\mathrm{d}_{in}t} * (FC_{\mathrm{d}_{in}t}) + \sum_{i}\sum_{t}\sum_{k'} BX_{\mathrm{d}_{out}t} * (Y_{k'\mathrm{d}_{out}ct}) + \sum_{\mathrm{d}_{out}}\sum_{p}\sum_{t} sl_{\mathrm{d}_{out}pt} * B_{\mathrm{d}_{out}pt} \\
& + \sum_{\mathrm{d}_{in}}\sum_{s}\sum_{T}\sum_{k} TC_{ks} * tC_s * X_{k\mathrm{d}_{in}st} + \sum_{k}\sum_{s}\sum_{s1}\sum_{t} XX_{kss_1t} * tC_s * C_k * D_{ss'})
\end{aligned}
\tag{1}
$$

$$
\mathrm{Min}\,Z2 = \sum_{k,k'}\sum_{\mathrm{d}_{in}}\sum_{c}\sum_{s}\sum_{t}\sum_{s1\neq s}\sum_{j1\neq j} rsk_k * (Y_{k\mathrm{d}_{in}ct} + X_{k\mathrm{d}_{in}st} + XX_{kss_1t}) + rsk_{k'} * YY_{k'\mathrm{d}_{out}cc_1t}) + \sum_{c}(pe * ye_c + pl * yl_c))
\tag{2}
$$

s.t

(3)

$$\sum_{p} Q_{pksd_{in}t} * VP_p + \sum_{p} \sum_{s_1 \neq s} QQ_{pkss_1t} * VP_p \leq VV_k \qquad \forall k, s, d_{in}, t$$

(4)

$$\sum_{p} \sum_{s} \sum_{k} Q_{pksd_{in}t} * VP_p + \sum_{p} SH_{d_{in}p(T-1)} * VP_p \leq V_{d_{in}} \qquad \forall d_{in}, t$$

(5)

$$\sum_{s} \sum_{k} Q_{pksd_{in}t} = \sum_{c} \sum_{k\prime} QP_{pk\prime d_{out}ct} + \sum_{k\prime} \sum_{c} \sum_{c_1 \neq c} QPT_{pk\prime d_{out}cc_1t} + sl_{d_{out}pt} \ \forall d_{in}, d_{out}, t, p$$

(6)

$$\sum_{r} QP_{pk\prime d_{out}ct} * VP_p + \sum_{r} \sum_{c_1 \neq c} QPT_{pk\prime d_{out}cc_1t} * VP_p \leq VV_{k'} \qquad \forall k', c, d_{out}, t$$

(7)

$$\sum_{k\prime} \sum_{d_{out}} QP_{pk\prime d_{out}ct} + \sum_{k\prime} \sum_{j_1 \neq j} \sum_{d_{out}} QPT_{pk\prime d_{out}c_1ct} + sl_{d_{out}pt} = D_{cpt} \qquad \forall p, c, t$$

(8)

$$\sum_{p} Q_{pksd_{in}t} \leq U * XXX_{ksd_{in}t} \qquad \forall k, d_{in}, s, t$$

(9)

$$\sum_{p} QQ_{pkss_1t} \leq U * XX_{kss_1t} \qquad \forall k, s, s_1, t;\ s_1 \neq s$$

(10)

$$\sum_{p} Q_{pksd_{in}t} + \sum_{s_1 \neq s} \sum_{r} QQ_{pkss_1t} \leq U * X_{kd_{in}st} \qquad \forall k, d_{in}, s, t$$

(11)

$$\sum_{d_{in}} X_{kd_{in}st} = \sum_{s_1 \neq s} XX_{kss_1t} + \sum_{d_{in}} XXX_{ksd_{in}t} \qquad \forall k, s, t$$

(12)

$$\sum_{d_{in}} \sum_{k} X_{kd_{in}st} + \sum_{s_1 \neq s} \sum_{k} XX_{ks_1st} \leq 1 \qquad \forall s, t$$

(13)

$$\sum_{d_{out}} \sum_{k} Y_{k\prime d_{out}ct} + \sum_{c_1 \neq c} \sum_{k} \sum_{d_{out}} YY_{k\prime d_{out}c_1ct} \leq 1 \qquad \forall c, t$$

(14)

$$\sum_{d_{in}} XXX_{ksd_{in}t} \leq 1 \qquad \forall s, k, t$$

(15)

$$\sum_{c_1 \neq c} \sum_{k\prime} \sum_{d_{out}} YY_{k\prime d_{out}cc_1t} + \sum_{d_{out}} \sum_{k\prime} YYY_{k\prime cd_{out}t} \leq 1 \qquad \forall c, t$$

(16)

$$\sum_{c} Y_{k\prime d_{out}ct} \geq \sum_{c} YYY_{k\prime cd_{out}t} \qquad \forall d_{out}, t, k'$$

(17)

$$\sum_{k} \sum_{s} XXX_{ksd_{in}t} = \sum_{c} \sum_{k\prime} Y_{k\prime d_{out}ct} \qquad \forall t, d_{in}, d_{out}$$

(18)

$$\sum_{k\prime} \sum_{c} Y_{k\prime d_{out}ct} \leq 1 \qquad \forall d_{out}, t$$

(19)

$$\sum_{p} QP_{pk'\mathrm{d}_{out}ct} \leq U * Y_{k'\mathrm{d}_{out}ct} \qquad \forall k', \mathrm{d}_{out}, c, t$$

(20)

$$\sum_{k'} \sum_{c_1 \neq c} \sum_{p} QPT_{pk'\mathrm{d}_{out}cc_1t} \leq U * YY_{k'\mathrm{d}_{out}cc_1t} \qquad \forall k', c1 \neq c, \mathrm{d}_{out}, c, t$$

(21)

$$YY_{k'\mathrm{d}_{out}cc_1t} + YY_{k'\mathrm{d}_{out}c1ct} \leq 1 \qquad \forall\, k', c, c1 \neq c, t, \mathrm{d}_{out}$$

(22)

$$\sum_{p} \sum_{k'} \sum_{c} QP_{pk'\mathrm{d}_{out}ct} \leq U * BX_{\mathrm{d}_{out}t} \qquad \forall\, \mathrm{d}_{out}, t$$

(23)

$$\sum_{p} \sum_{k} \sum_{s} Q_{pks\mathrm{d}_{in}t} \leq U * BX_{\mathrm{d}_{in}t} \qquad \forall\, \mathrm{d}_{in}, t$$

(24)

$$Y_{k'\mathrm{d}_{out}ct} + \sum_{c_1 \neq c} YY_{k'\mathrm{d}_{out}c_1ct} = \sum_{c_1 \neq c} YY_{k'\mathrm{d}_{out}cc_1t} + \sum_{i} YYY_{k'c\mathrm{d}_{out}t} \qquad \forall\, k', \mathrm{d}_{out}, c, t$$

- Constraint (1) ensures the maximization of revenue from the sale of products taking into account perishable product type discounts, the costs of supplying products from the supplier, sending the sorted products in the cross-dock to the customer, supplying the products from the second supplier to the cross-dock, sending products from one customer to another, fixed costs of supplying and distributing products to customers through the cross-dock, sorting costs, fixed costs of locating entrance and exit doors of the cross-dock, and the costs of vehicle transportation to the supplier.
- Constraint (2) ensures the minimization of the risk of using the vehicles and the scheduling of sending the products to the customers.
- Constraint (3) ensures that the total product received from all suppliers is less than the transporting capacity of the used vehicle.
- Constraint (4) ensures that the total product received in the cross-dock is less than the volume of the cross-dock.
- Constraint (5) ensures that the balance of products in the cross-dock is such that all inbound products are transferred to the demanding customers at any time.
- Constraint (6) ensures that the total volume of loaded products is less than the volume of the vehicles to deliver products to the customer and does not exceed the capacity of the vehicles.
- Constraint (7) ensures that all customers' demands are either received directly from the cross-dock or sent from one customer to another.
- Constraint (8) ensures that the route between the cross-dock and the supplier is opened if the product is received from a supplier.
- Constraint (9) ensures that the route between two suppliers is opened if the product is moved from one supplier to another.
- Constraint (10) ensures that the route between the cross-dock and the supplier is opened if the product is moved from the supplier to the cross-dock or from one supplier to another.
- Constraint (11) ensures that either the vehicle will move to the next supplier or it will load and return the product to the cross-dock as much as the available volume of the vehicle at time t if the vehicle moves to the supplier at the same time.

- Constraint (12) ensures that a supplier is allowed to enter a vehicle only once at any time.
- Constraint (13) ensures that the route is opened either from the cross-dock to the customer or from one customer to another at any time.
- Constraint (14) ensures that at most one vehicle moves from the supplier to the cross-dock at any time.
- Constraint (15) ensures that the vehicle arriving at each customer either moves to the next customer or returns to the cross-dock at any time.
- Constraint (16) ensures that the vehicle will return from the customer to the cross-dock if possible if it moves from the cross-dock to the customer.
- Constraint (17) ensures that the products leave the cross-dock at the same time as they enter the cross-dock from the supplier.
- Constraint (18) ensures that the vehicle can move from the cross-dock to the customer once at any time.
- Constraint (19) ensures that the route between the cross-dock and the customer is opened if the products are sent from the cross-dock to the customer at any time.
- Constraint (20) ensures that the route is opened between customers if the products are moved between them.
- Constraint (21) ensures that no closed loop is created between customers.
- Constraint (22) ensures that the exit door of the cross-dock is located if the products are sent to customers at any time from the exit door of the cross-dock.
- Constraint (23) ensures that the entrance door of the cross-dock is located if the products are sent to customers at any time from the entrance door of the cross-dock.
- Constraint (24) ensures that the inbound and outbound vehicles to each customer are balanced.

3. Model Validation

Table 2 shows a small sample problem according to the problem size. Deterministic and non-deterministic parameters for solving the problem can be seen in Table 3. The data were obtained according to the opinions of experts in the Iranian food industry and using the studies published in this field based on uniform distribution.

Table 2. Small sample problem

Set	Symbol	Number	Set	Symbol	Number
Suppliers	S	3	Products	P	2
Customers	C	5	Time window	T	2
Vehicles	k	3			

Table 3. The deterministic parameters used in the problem based on uniform distribution

Parameter	Range limits	Parameter	Range limits
CV_k	~U (20,000, 30,000)	D_{cpt}	~U (300, 500)
C_k	~U (50,000، 60,000)	tC_s	~U (500, 800)
TC_{ks}	~U (200, 300)	$price_{pst}$	~U (10, 20)
D_s	~U (10, 20)	$FC_{d_{in}t}$	~U (10, 20)
TSp	~U (10, 15)	T_c	~U (10, 20)
VV_k	100	SS_p	~U (10, 20)

3.1. LP-Metric Method

LP-Metric is one of the prominent decision-making techniques in multi-objective optimization problems with incompatible objectives. In this technique, the multi-objective problem becomes a single-objective problem by using the optimal values of the existing objective functions and the weights provided by the decision-maker according to Equation (25).

$$minD = \left(\sum_{p=1}^{P} w_p \left(\frac{f_p^* - f_p}{f_p^*}\right)^r\right)^{1/r} \quad (25)$$

where r indicates the norm of the problem, which is usually 1, and wp indicates the preferred weight of the objective functions, whose sum must be 1.
3.2. Numerical Example
In the following, the small sample problem is solved using the solution methods described in the previous section. The value of the objective function, the optimal location of facilities, and the optimal vehicle routing of the single-objective model (the first objective function) for the small sample problem can be seen in Table 4.

Table 4. The optimal location of potential facilities and transportation routing considering the first objective function by individual optimization

Potential centers	Number	Optimal location
Suppliers	2 centers	2 and 3
Customers	2 centers	A and C
Optimal vehicle routing	Vehicle 1 at time 1	$A \to 1 \to 4 \to A$
	Vehicle 2 at time 1	$C \to 3 \to 2 \to 5 \to C$
	Vehicle 1 at time 2	$A \to 4 \to 3 \to A$
	Vehicle 2 at time 2	$C \to 2 \to 5 \to 1 \to C$
The value of the first objective function		541,633.336

The value of the objective function, the optimal location of facilities, and the optimal vehicle routing of the single-objective model (the second objective function) for the small sample problem can be seen in Table 5.

Table 5. The optimal location of potential facilities and transportation routing considering the second objective function by individual optimization

Potential centers	Number	Optimal location
Suppliers	3 centers	1, 2, and 3
Customers	3 centers	B *and* C
Optimal vehicle routing	Vehicle 1 at time 1	$B \to 3 \to 1 \to B$
	Vehicle 2 at time 1	$C \to 2 \to 4 \to 5 \to A$
	Vehicle 1 at time 2	$B \to 3 \to 1 \to B$
	Vehicle 2 at time 2	$C \to 2 \to 4 \to 5 \to A$
The value of the second objective function		44,942.651

After determining the best value of the first and second objective functions for the small problem, the set of efficient solutions resulting from solving the problem with multi-objective decision-making methods (LP-metric) is provided. The set of efficient solutions for the small sample problem using the LP-metric can be seen in Table 6.

Table 6. The set of efficient solutions resulting from solving the small sample problem using the LP-metric

Efficient solutions	The first objective function	The second objective function	Computational time
1	575,779.95	50,051.23	
2	655,412.43	50,223.64	
3	552,152.40	51,102.23	498.31
4	546,081.87	52,404.25	
5	541,713.27	53,993.55	

The Pareto front could be drawn according to the efficient solutions obtained from solving the small sample problem. The Pareto front resulting from solving the small sample problem with multi-objective decision-making methods is given in Figure 3.

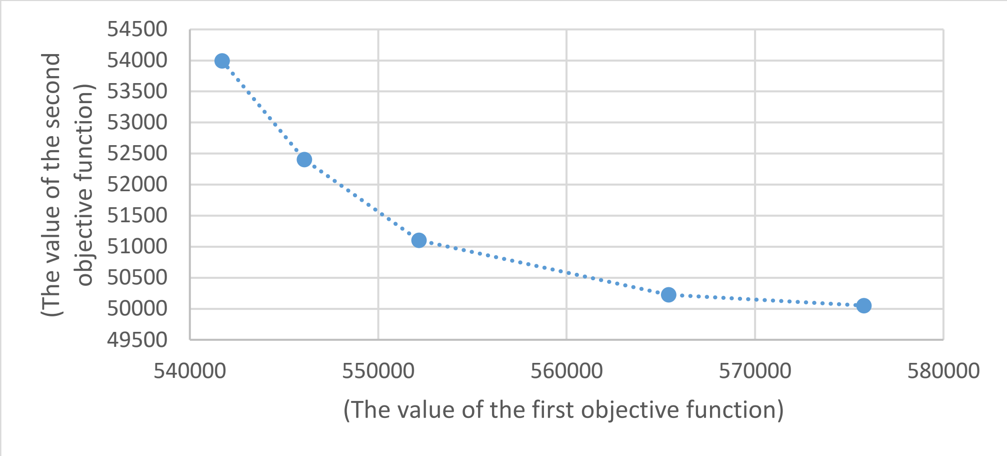

Figure 3. The Pareto front resulting from solving the small sample problem with multi-objective decision-making methods

Table 7 shows the location of facilities and the optimal vehicle routing resulting from the solution of the sample problem using the LP-metric to check the output variables of the problem.

Table 7. The location of potential facilities and vehicle routing resulting from solving the small problem using the LP-metric

Potential centers	Number	Optimal location
Suppliers	2 centers	2 and 3
Customers	2 centers	B and C
Optimal vehicle routing	Vehicle 1 at time 1	$B \rightarrow 3 \rightarrow 1 \rightarrow B$
	Vehicle 2 at time 1	$C \rightarrow 2 \rightarrow 4 \rightarrow 5 \rightarrow C$
	Vehicle 1 at time 2	$B \rightarrow 3 \rightarrow 1 \rightarrow B$
	Vehicle 2 at time 2	$C \rightarrow 2 \rightarrow 4 \rightarrow 5 \rightarrow C$

4. The Meta-heuristic algorithms

In this section, the meta-heuristic NSGA-II and MOPSO algorithms with priority-based encoding-decoding are used to solve larger sample problems. So, the initial solution used to solve the problem and the meta-heuristic algorithm operators are first provided. The parameters of meta-heuristic algorithms are then tuned using the Taguchi method.

4.1. Primary Chromosome

In this study, a novel priority-based encoding-decoding was used due to the high complexity of the proposed model. This encoding-decoding is based on a permutation of natural numbers with a length equal to the number of nodes in each level. The modified priority-based encoding-decoding for one network level with 3 suppliers and 4 customers can be seen in Figure 4. The encoding-decoding in one of the levels of the supply chain network with 3 suppliers and 4 customers is shown in Figure 4. The encoding-decoding is based on a permutation of the number of nodes shown in Figure 4 as (2-5-3-7-4-1-6). The priorities (6-1-4-7) belong to the customers and the priorities (3-5-2) belong to the suppliers. The following two steps must be taken for encoding-decoding: **Step 1**. The highest priority is first selected among the suppliers (priority 5 corresponding to the second supplier). The priority of the other centers will be reduced to zero if this supplier can meet all the demands of the customers. In this case, the next supplier with the next highest priority (priority 3 corresponding to the third supplier) is selected. The total capacity of the two suppliers (1650) is greater than the total customer demand (1300). In this case, only the first supplier's priority will be reduced to zero**. Step 2**. After determining the number and location of potential suppliers, the optimal allocation is made between the selected suppliers and the customers. The highest priority (priority 7 corresponding to the customer) is selected, and the lowest transportation cost corresponding to this customer is identified with the supplier selected from the first step (the third supplier with a cost of 15). The minimum supplier capacity value is selected, and the designated supplier is identified as the optimal allocation value. The priority value is reduced to zero after updating the remaining capacity or unmet demand. The second step is repeated until the values of all the priorities are reduced to zero.

Node	fixed construction cost	Capacity	Demand
1	11000	800	300
2	9000	950	350
3	10000	700	300
4	-	-	350

	Transportation cost			
Node	1	2	3	4
1	11	19	17	18
2	16	14	18	15
3	15	16	19	13

$v(K+J)$

Node	1	2	3	1	2	3	4
Priority	2	5	3	7	4	1	6

$v(K+J)$

Node	1	2	3	1	2	3	4
Priority	0	5	3	7	4	1	6

Total cost = 38350

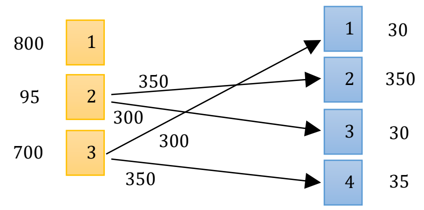

Figure 4. Modified priority-based encoding-decoding

4.2. Parameter tuning of meta-heuristic algorithms

The parameters were tuned using the response variable. This variable is a combination of the 5 criteria provided, and its value is calculated using the following equation. Since the measures are not of equal importance, the weight factors used are determined for them based on Equation (26).

$$R_i = \frac{\overline{NPF_1} + \overline{MSI_2} + \overline{SM_3} + \overline{Time}}{w_1 + w_2 + w_3 + w_4} \tag{26}$$

4.3. Factors and factor levels of the NSGA-II algorithm

The NSGA-II algorithm factors and levels are given in Table 8.

Table 8. The factor levels used for the NSGA-II algorithm

	Factor levels		
Parameters	**1**	**2**	**3**
nPop	50	70	100
pc	0.2	0.5	0.8
pm	0.2	0.3	0.4

The orthogonal arrays L9 (34) are selected as the most suitable design for Models 3 to 6 by referring to the standard table of orthogonal arrays in the Taguchi method and using Minitab software. The orthogonal arrays of this design can be seen in Table 9.

Table 9. The orthogonal arrays L9 (34) for the NSGA-II algorithm

The experiment number	nPop	Pc	Pm
1	1	1	1
2	1	2	2
3	1	3	3
4	2	1	2
5	2	2	3
6	2	3	1
7	3	1	3
8	3	2	1
9	3	3	2

Since the value of Ri is different in each problem and cannot be used directly, the relative percent difference (RPD) is used for each problem.

$$\mathrm{RPD} = \frac{\mathrm{Alg_{sol}} - \mathrm{Min_{sol}}}{\mathrm{Min_{sol}}} \times 100 \tag{27}$$

Where Algsol and Minsol are the Ri values for each iteration of the experiment and the best solution, respectively. After converting the Ri value to RPD, the S/N ratio is calculated based on RPD according to the design structure of the Taguchi parameter. The mean S/N ratio of the experiments is then calculated for each parameter level. The best value of each parameter has the lowest value of the mean of means. Optimal factor levels are those that result in a minimum mean ratio. Figures 5 and 6 show the results of the mean of means and mean S/N ratio for each factor level in the NSGA-II algorithm for the proposed model after performing the Taguchi experiment.

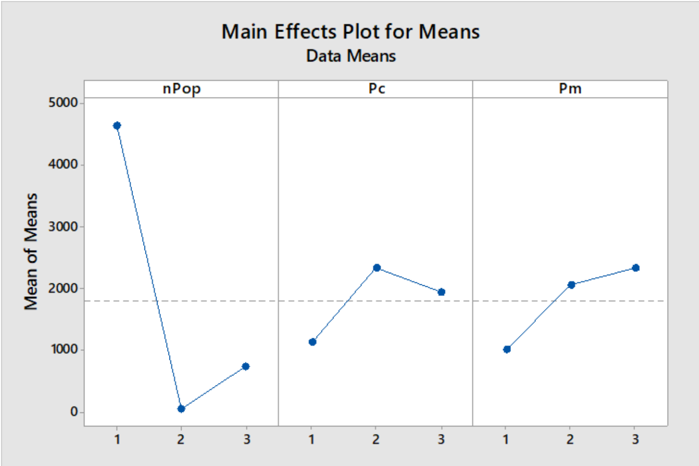

Figure 5. The plot of the mean of means for the NSGA-II algorithm

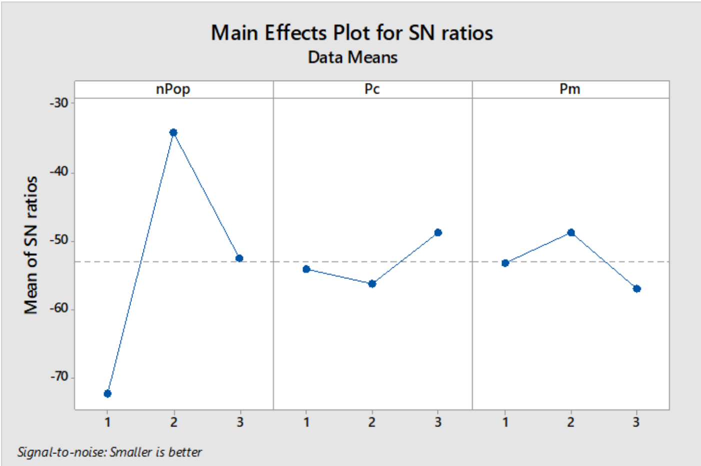

Figure 6. The plot of the mean S/N ratio for the NSGA-II algorithm

According to the obtained plots, the optimal factor levels for the NSGA-II algorithm are as follows:

Table 10. The optimal factor levels used for the NSGA-II algorithm

	Factor level			Optimal factor level
Parameters	1	2	3	
nPop	50	70	100	70
pc	0.2	0.5	0.8	0.2
pm	0.2	0.3	0.4	0.2

4.4. Factors and factor levels of the MOPSO algorithm

As with the NSGA-II algorithm, the factors and factor levels used for the MOPSO algorithm are defined according to Table 11. The orthogonal arrays in Table 12 are defined in Table 11.

Table 11. The factor levels used for the MOPSO algorithm

	Factor level		
Parameters	1	2	3
nPop	50	75	100
nRep	70	100	150
W	0.5	0.6	0.7
C1	1	1.25	1.5
C2	1	1.25	1.5

Table12. The orthogonal arrays L9 (35) for the MOPSO algorithm

The experiment number	nPop	nRep	W	C1	C2
1	1	1	1	1	1
2	1	1	1	1	2
3	1	1	1	1	3
4	1	2	2	2	1
5	1	2	2	2	2
6	1	2	2	2	3
7	1	3	3	3	1
8	1	3	3	3	2
9	1	3	3	3	3
10	2	1	1	1	1
11	2	1	1	1	2
12	2	1	1	1	3
13	2	2	2	2	1
14	2	2	2	2	2
15	2	2	2	2	3
16	2	3	3	3	1
17	2	3	3	3	2
18	2	3	3	3	3
19	3	1	1	1	1
20	3	1	1	1	2
21	3	1	1	1	3
22	3	2	2	2	1
23	3	2	2	2	2
24	3	2	2	2	3
25	3	3	3	3	1
26	3	3	3	3	2
27	3	3	3	3	3

Figures 7 and 8 show the results of the mean of means and the mean S/N ratio for each factor level in the MOPSO algorithm for the proposed model after performing the Taguchi experiment.

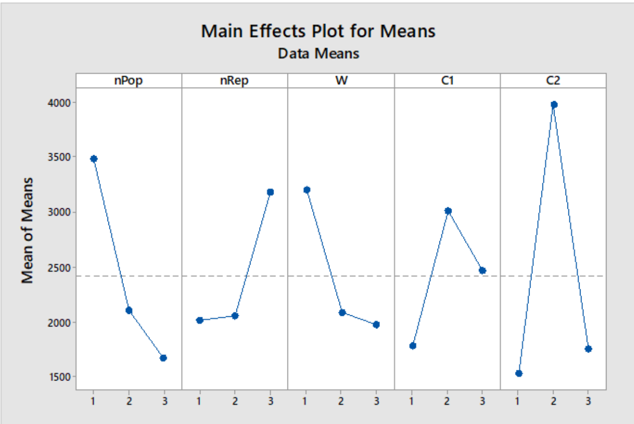

Figure 7. The plot of the mean of means for the MOPSO algorithm

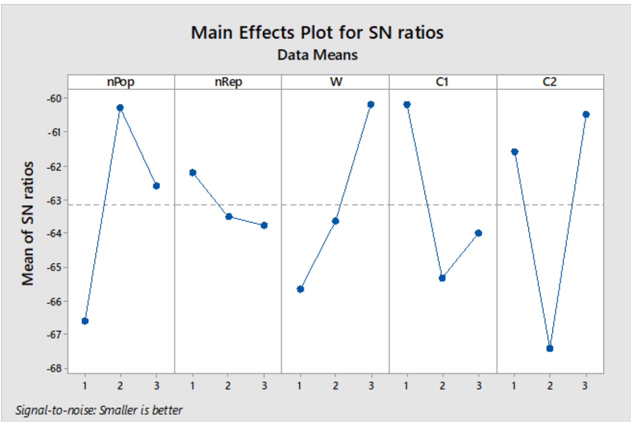

Figure 8. The plot of the mean S/N ratio for the MOPSO algorithm

According to the obtained plots, the optimal factor levels for the MOPSO algorithm are as follows:

Table 13. The optimal factor levels used for the MOPSO algorithm

	Factor level			Optimal factor level
Parameters	1	2	3	
nPop	50	75	100	100
nRep	70	100	150	70
W	0.5	0.6	0.7	0.7
C1	1	1.25	1.5	1
C2	1	1.25	1.5	1

4.5. Evaluation of NSGA-II and MOPSO algorithms

A small sample problem is designed for the proposed algorithms and the output variables from the first efficient solution of each algorithm are shown to evaluate and determine the coding accuracy performed in MATLAB software. So, the size of the problem determined in the initial validation is based on stochastic parameters generated by the uniform distribution according to Tables 2 and 3. After designing the problem and generating random data, the problem is solved using meta-heuristic algorithms in 100 iterations, and the comparison indices of multi-objective meta-heuristic algorithms are determined for each algorithm. The means and indices of the results obtained from the execution of NSGA-II and MOPSO algorithms are given in Table 14.

Table 14. Comparison indices of meta-heuristic algorithms in solving the sample problem

Index	NSGA-II algorithm	MOPSO algorithm
Computational time	18.88	6.64
The mean first objective function	573954.21	569563.94
The mean second objective function	49622.11	49371.86
NPF	10	9
MSI	36643.30	35751.92
SM	0.476	0.381

As can be seen in Table 14, the computational time obtained from solving the sample problem with the MOPSO algorithm is less than the NSGA-II algorithm. However, the NSGA-II algorithm performs better than the MOPSO algorithm in finding the number of efficient solutions. Figure 9 shows the Pareto front obtained from solving the sample problem with NSGA-II and MOPSO algorithms.

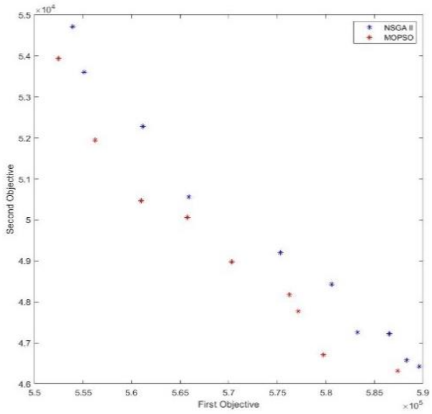

Figure 9. Pareto front resulting from solving the small problem with NSGA-II and MOPSO algorithms

Table 15 shows the number and optimal location of facilities and the optimal route obtained from solving the problem with two algorithms for the first efficient solution of the problem to show the important outputs of the supply chain model under study.

Table 15. The number and optimal location of facilities and optimal vehicle routing with meta-heuristic algorithms

Algorithm	Potential centers	Number	Optimal location
NSGA-II	Suppliers	2 centers	1 and 3
	Customers	2 centers	$A\ and\ C$
	Optimal vehicle routing	Vehicle 1 at time 1	$C \to 3 \to 4 \to C$
		Vehicle 2 at time 1	$A \to 5 \to 1 \to 2 \to A$
		Vehicle 1 at time 2	$C \to 2 \to 5 \to C$
		Vehicle 2 at time 2	$A \to 4 \to 3 \to 1 \to A$
MOPSO	Suppliers	2 centers	1 and 2
	Customers	2 centers	$A\ and\ B$
	Optimal vehicle routing	Vehicle 1 at time 1	$B \to 3 \to 2 \to B$
		Vehicle 2 at time 1	$A \to 1 \to 4 \to 5 \to A$
		Vehicle 1 at time 2	$B \to 1 \to 4 \to B$
		Vehicle 2 at time 2	$A \to 5 \to 2 \to 3 \to A$

4.6. Solving larger sample problems with MOPSO and NSGA-II algorithms

In this section, 15 sample problems (Table 16) are designed based on stochastic data by a uniform distribution to solve larger sample problems. From each sample problem, 5 problems with the same size are designed in the defined data range, and the mean of each index is evaluated as a basis for comparison.

Table 16. Larger sample problems

Sample problem	j	k	l, l'	m, c	p	t	v
1	4	4	6	8	2	4	4
2	6	4	6	9	3	4	4
3	6	4	7	10	3	4	4
4	10	5	8	12	3	4	5
5	12	10	9	16	3	5	5
6	15	12	11	17	4	5	6
7	15	14	12	18	4	5	6
8	15	15	12	20	5	5	6
9	16	16	13	21	5	6	7
10	16	16	14	24	5	6	7
11	17	16	15	25	5	6	7
12	18	17	15	26	7	7	7
13	19	17	16	27	7	7	8
14	19	17	16	28	7	8	8
15	20	20	20	30	8	8	8

To solve each sample problem, 5 other problems of the same size are designed and solved with NSGA-II and MOPSO algorithms, and the mean results are used as a basis for comparison to avoid stochastic data generation. The mean objective functions and comparison indices of meta-heuristic algorithms for each sample problem can be seen in Tables 17 and 18, respectively.

Table 17. Mean objective functions and comparison indices in solution with the NSGA-II algorithm

Sample problem	The first objective functions	The second objective functions	The number of efficient solutions	Maximum spread	Spacing	Computational time
1	633,806.72	62,601.70	9	270,273.91	0.37	36.46
2	778,692.87	78,381.54	19	585,593.25	0.77	108.00
3	881,581.31	85,446.74	20	479,316.63	0.70	170.30
4	1,033,814.58	90,080.84	14	850,298.87	0.57	242.53
5	1,674,913.50	103,382.09	14	1,129,077.89	0.41	335.50
6	2,369,557.62	114,251.75	22	1,511,575.10	0.55	434.40
7	2,500,890.63	125,543.40	23	1,797,128.03	0.53	545.77
8	3,416,474.10	132,080.49	18	2,739,770.14	0.57	669.07
9	4,301,935.98	140,272.83	21	2,529,228.60	0.40	819.60
10	4,860,023.44	159,821.22	23	3,529,017.44	0.75	959.67
11	5,040,590.70	163,061.03	23	3,087,180.76	0.74	1,040.13
12	8,540,218.42	178,342.69	23	4,883,033.12	0.69	1326.00
13	8,887,924.17	182,872.57	30	3,839,628.23	0.66	1528.37
14	10,361,985.83	193,154.36	21	4,561,422.62	0.77	1802.27
15	12,608,666.41	207,290.80	24	5,383,709.71	0.87	2640.00

Table 18. Mean objective functions and comparison indices in solution with the MOPSO algorithm

Sample problem	The first objective functions	The second objective functions	The number of efficient solutions	Maximum spread	Spacing	Computational time
1	635,858.69	60,567.22	8	109,850.13	0.46	34.40
2	776,699.89	71,074.60	14	329,845.53	0.62	39.07
3	871,134.25	89,693.95	8	370,471.43	0.23	51.66
4	1,046,187.49	94,437.00	16	463,108.57	0.59	95.93
5	1,653,146.41	107,002.93	18	817,523.73	0.35	131.20
6	2,353,344.22	115,415.91	23	1,526,123.67	0.49	280.50
7	2,450,251.68	123,910.36	16	2,008,648.76	0.55	349.16
8	3,334,001.90	136,349.08	31	2,559,860.14	0.75	494.70
9	4,334,688.39	148,225.98	28	3,694,417.30	0.64	723.16
10	4,817,592.14	151,730.43	19	2,215,230.18	0.59	980.40
11	5,120,556.34	165,792.57	12	2,437,807.90	0.76	1328.75
12	8,500,502.39	175,673.57	25	3,887,334.58	0.44	1834.56
13	8,759,033.18	187,113.32	12	3,757,576.19	0.72	2337.30
14	10,251,098.76	192,138.59	12	4,593,286.90	0.66	2983.04
15	12,554,017.27	207,281.68	17	5,138,916.08	0.51	3957.90

The means of objective functions and the comparison indices of meta-heuristic algorithms in each sample problem with NSGA-II and MOPSO algorithms are shown in Tables 17 and 18.

In the previous section, the sample problems were solved using the NSGA-II and MOPSO algorithms. In this section, the TOPSIS technique is used to select the most efficient algorithm. The overall means of the 15 sample problems can be seen in Table 18 and 19.

Table 19. The means of the indices obtained from meta-heuristic algorithms

Algorithm	The first objective functions	The second objective functions	The number of efficient solutions	Maximum spread	Spacing	Computational time
NSGA-II	4,526,072	134,439	20.27	2,478,417	0.623	844
MOPSO	4,497,208	135,094	17.27	2,260,667	0.557	1,041
Weight	0.4	0.4	0.05	0.05	0.05	0.05

After descaling the results in Table 19, the results indicate the better performance of the NSGA-II algorithm with a weight of 0.6945 compared to the MOPSO algorithm with a weight of 0.3055. Considering all the indices and results, the use of NSGA-II algorithm is recommended.

5. Conclusions

One of the most important areas in any country is the dairy industry, which is introduced as a system consisting of processes, operations, and organizations in the development and formation stage. Meanwhile, one of the most important strategic issues in the food industry is the supply chain in the dairy sector because supply chain costs directly affect the costs of dairy products. The dairy supply chain refers to the path through which high-quality products are distributed to end consumers at the right place and time. Dairy companies ignored the concept of SCM in the past. However, today's companies are forced to change their traditional business methods due to several factors, one of which is the supply chain, which is becoming a competitive advantage. This study developed a multi-objective optimization model for the dairy perishable food supply chain, incorporating a novel stepwise pricing mechanism based on product shelf-life. The main contributions of this research include: (i) realistic modeling of price-perishability relationships that capture revenue loss due to spoilage, (ii) integration of financial risk assessment in purchase and distribution decisions, and (iii) development of an effective solution methodology using NSGA-II and MOPSO algorithms with modified priority-based encoding-decoding. NSGA-II and MOPSO algorithms with modified priority-based encoding-decoding were used due to the inefficiency of GAMS software in solving large problems. The initial parameters of the meta-heuristic algorithms were first tuned using the Taguchi method, and 15 larger sample problems were then designed. Five problems of the same size were designed to prevent the generation of incorrect random data, and the means of the objective functions and comparison indexes of meta-heuristic algorithms (the number of efficient solutions, maximum spread, spacing, and computational time) were analyzed as the basis of evaluation and comparison. The TOPSIS technique was then used to determine the most efficient algorithm. Key findings indicate that the NSGA-II algorithm with a weight of 0.6945 significantly outperforms the MOPSO algorithm with a weight of 0.3055, demonstrating superior performance in solution quality and diversity metrics across all problem sizes. Therefore, the use of the NSGA-II algorithm is recommended considering all the indices and results.

Future research directions include: (i) incorporating robust optimization to handle parameter uncertainty, (ii) extending the model to include sustainability objectives (environmental and social dimensions), (iii) considering multi-period dynamic pricing strategies, and (iv) applying the model to real-world case studies for practical validation.

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