International Journal of Industrial Engineering & Production Research

RESEARCH PAPER

An Optimization Model for Carbon-Constrained Fresh Agri-Food E-Commerce Supply Chains: A Genetic Algorithm and Particle Swarm Optimization Approach

Novrianty Rizky[1], Elisa Kusrini[2], Agus Mansur[3]*, Muhammad Ridwan Andi Purnomo[4]

Received xxx; Revised xxx; Accepted xxx;
© Iran University of Science and Technology 2025

ABSTRACT

Fresh agri-food e-commerce operates through complex multi-echelon supply chains, where perishability and transportation increase both operational costs and carbon emissions. Although previous studies have relied on mixed-integer linear programming (MILP) and exact optimization methods, the performance of metaheuristics under carbon-constrained conditions remains largely unexplored. This study extends a carbon-constrained MILP model by incorporating single-sourcing decisions and a planning-horizon emission cap. A feasibility-preserving random-key decoder with a shadow carbon price gene is embedded into Genetic Algorithm (GA) and Particle Swarm Optimization (PSO), both calibrated using a Taguchi L9 design. In a real case study in Java, Indonesia, PSO achieved IDR 605.67 billion, only 0.44% below the exact optimum of IDR 608.33 billion, whereas GA recorded a 5.19% gap. PSO significantly outperformed GA (Mann-Whitney U test, $p = 0.0002$). The proposed framework provides a solver-independent approach for carbon-constrained agri-food supply chain optimization.

KEYWORDS: *Mixed-integer linear programming; Agri-food; Food loss and waste; Carbon cap; Genetic algorithm; Particle swarm optimization*

1. Introduction

The rapid expansion of e-commerce has transformed the distribution of fresh agricultural products in Indonesia. An increasing proportion of fruits and vegetables are now purchased through online marketplaces and mobile applications, particularly in major urban areas where consumers demand convenient home delivery and short lead times. To accommodate this shift in purchasing behavior, retailers and distributors have adopted dual-channel distribution systems that combine conventional retail outlets with online sales platforms. Although this business model improves market accessibility, it also extends supply chain complexity by introducing additional warehousing activities and last-mile delivery operations, which are predominantly served by motorcycles.

Despite the growth of online agri-food retailing, food loss and waste (FLW) remain a critical challenge throughout the supply chain. According to the Food and Agriculture Organization (FAO), approximately one-third of all food produced globally, equivalent to 1.3 billion tonnes annually, is either lost or wasted before consumption [1]. Beyond the direct loss of food, FLW represents a substantial waste of land, water, energy, labor, and other production resources [2]. Indonesia is recognized as the largest contributor of household food waste in Southeast Asia [3], generating approximately 20.93 million tonnes of food waste each year [4]. Furthermore, a national assessment estimated that total food loss and waste ranged from 23 to 48 million tonnes annually between 2000 and 2019, resulting in economic losses of IDR 213–551 trillion, or approximately 4–5% of the national gross domestic product (GDP) [5].

The environmental consequences of FLW further emphasize the need for sustainable supply chain planning. Globally, FLW contributes approximately 8–10% of total greenhouse gas emissions [3]. Organic waste disposed of in landfills generates methane, whose global warming potential is approximately 25 times greater than that of carbon dioxide [2]. In addition, products that deteriorate during transportation embody unnecessary fuel consumption and associated transport emissions. Consequently, reducing food waste not only improves resource utilization but also contributes to lower operating costs and reduced carbon emissions across the supply chain [6].

* *Corresponding author: Agus Mansur*
agusmansur@uii.ac.id

1. *Department of Industrial Engineering, Faculty of Industrial Technology, Universitas Islam Indonesia*
2. *Department of Industrial Engineering, Faculty of Industrial Technology, Universitas Islam Indonesia*
3. *Department of Industrial Engineering, Faculty of Industrial Technology, Universitas Islam Indonesia*
4. *Department of Industrial Engineering, Faculty of Industrial Technology, Universitas Islam Indonesia*

[Downloaded from ijiepr.iust.ac.ir on 2026-01-06]

To address these challenges, numerous optimization models have been developed using mixed-integer linear programming (MILP). Previous studies, including our earlier work, formulated profit-oriented MILP models for fresh agri-food e-commerce networks in Java [7], while related studies optimized costs, food waste, and carbon emissions in fresh-food e-commerce [8], dairy [9], and fish supply chains [10]. Although exact optimization methods provide globally optimal solutions for linear models, their computational efficiency decreases as problem size and network complexity increase. Moreover, practical implementation often depends on commercial optimization software, limiting accessibility for many small and medium-sized enterprises (SMEs), which typically rely on spreadsheet-based decision support. In contrast, metaheuristic algorithms, such as the Genetic Algorithm (GA) [11] and Particle Swarm Optimization (PSO) [12], require only objective function evaluations, offer greater modeling flexibility, and can accommodate nonlinear relationships without extensive reformulation.

Although metaheuristic approaches have been widely applied to agri-food supply chain optimization, most existing studies focus primarily on cost minimization and are concentrated on case studies from Iran [13–16]. Comparatively few studies have investigated profit maximization under explicit carbon emission constraints or considered dual-channel fresh agri-food e-commerce networks. More importantly, previous research has rarely benchmarked the performance of GA and PSO against an exact optimal solution for a carbon-constrained supply chain model. Consequently, the solution quality, optimality gap, and practical applicability of these algorithms remain insufficiently understood. This limitation is particularly important for practitioners, who require reliable estimates of the economic trade-offs associated with adopting metaheuristic optimization methods instead of exact solvers.

Accordingly, this study addresses the following research questions:

RQ1. How closely can GA and PSO approximate the exact profit-maximizing solution for a carbon-constrained, single-sourcing fresh agri-food e-commerce supply chain, and which algorithm demonstrates optimization performance?
RQ2. How do variations in customer demand, selling price, and carbon emission limits influence optimal profit, food waste, and emissions under the best-performing metaheuristic algorithm?

This study makes four primary contributions. First, it extends an existing MILP model by incorporating single-sourcing decisions and a planning-horizon carbon emission constraint for fresh agri-food e-commerce supply chains. Second, it develops a feasibility-preserving priority-based random-key decoder integrated with a shadow carbon price gene to improve solution quality while maintaining model feasibility. Third, it systematically benchmarks GA and PSO against an exact MILP solution obtained in Python using a real-world case study in Java and three larger synthetic problem instances, thereby quantifying solution quality and scalability. Finally, it provides sensitivity analyses and managerial insights by evaluating the economic implications of carbon emission constraints and identifying the key parameters affecting supply chain profitability.

The remainder of this paper is organized as follows. Section 2 reviews the relevant literature and identifies the research gap. Section 3 describes the problem setting and supply chain configuration. Section 4 presents the model assumptions, notation, and mathematical formulation. Section 5 formulates the proposed MILP model. Section 6 presents the proposed metaheuristic solution approaches using the GA and PSO. Section 7 reports the computational results, comparative performance analysis, and sensitivity analysis. Section 8 discusses the managerial implications of the proposed approach. Finally, Section 9 concludes the paper and suggests directions for future research

2. Previous Work

MILP has become the dominant optimization approach for planning agri-food and other perishable supply chains because it can simultaneously determine procurement, production, inventory, and distribution decisions while guaranteeing global optimality. Recent studies have extended MILP models to incorporate multiple sustainability objectives, including economic performance, food waste reduction, carbon emission mitigation, product traceability, and reverse logistics. For example, Wangsa et al. [8] optimized fresh agri-food e-commerce supply chains by integrating food waste, carbon emissions, temperature control, drones, and electric motorcycles. Similar optimization frameworks have been developed for dairy [9], fish [10,17], blood [18], fresh produce [19,20], and closed-loop agri-food supply chains [21], demonstrating the flexibility of MILP for complex multi-echelon network design.

[Downloaded from ijiepr.iust.ac.ir on 2026-11-06]

Another major research direction focuses on incorporating uncertainty and supply chain resilience. Various optimization approaches have considered demand uncertainty, supply disruptions, pandemics, and fuzzy environments through robust optimization, stochastic programming, and fuzzy mathematical programming [22–30]. In addition, product deterioration has been extensively modeled by considering the combined effects of storage duration and temperature on product quality [31,32]. Recent studies have also investigated coordination mechanisms, blockchain-enabled traceability, channel competition, and collaborative planning in perishable supply chains [33–39]. Collectively, these studies demonstrate that exact optimization remains the preferred approach for solving strategic and tactical planning problems in agri-food systems. However, its computational performance deteriorates rapidly as network size, nonlinear relationships, and operational constraints increase.

To overcome the computational limitations of exact optimization methods, recent research has increasingly adopted metaheuristic algorithms for solving large-scale and computationally complex agri-food supply chain problems. Existing studies have applied various population-based and hybrid metaheuristics to optimize sustainable, circular, and closed-loop agri-food supply chains under uncertainty. Representative applications include shrimp [13], soybean [40], saffron [15], citrus [43], and other agricultural supply chains incorporating marketing decisions, freshness, government policies, and circular economy strategies [14,16,41,42,44]. Most of these studies primarily focused on minimizing total cost, transportation distance, or environmental impacts while considering offline distribution networks.

Among the available metaheuristics, GA and PSO remain the most widely adopted because of their simplicity, computational efficiency, and adaptability to large optimization problems. GA searches the solution space through evolutionary operators, including selection, crossover, and mutation [11,45], whereas PSO updates candidate solutions according to individual and global best experiences within the swarm [12,46]. For discrete optimization problems, random-key encoding combined with decoding procedures has become a common strategy for transforming continuous search spaces into feasible combinatorial solutions [47]. Likewise, simulated binary crossover [48] and feasibility-preserving constraint-handling techniques [49] have been widely employed to improve search efficiency while maintaining solution feasibility.

Despite these developments, existing metaheuristic studies rarely evaluate solution quality against certified optimal solutions obtained from exact optimization methods. Consequently, the optimality gap and practical reliability of metaheuristic solutions remain insufficiently quantified, particularly for carbon-constrained agri-food supply chain planning.

Table 1 summarizes the most relevant studies according to product type, distribution channel, environmental consideration, optimization objective, and solution approach. Several important research gaps can be identified.

- First, previous Indonesian studies on fresh agri-food supply chains predominantly relied on exact MILP formulations solved using commercial optimization software [7–10,17,18], without investigating the effectiveness of metaheuristic approaches for solving the same optimization problem.
- Second, although numerous metaheuristic studies have addressed sustainable agri-food supply chain optimization [13–16,40–44], they mainly focused on cost minimization within conventional offline distribution systems. Profit maximization under explicit carbon emission constraints in dual-channel fresh agri-food e-commerce networks has received very limited attention.
- Third, existing research rarely benchmarks metaheuristic algorithms against certified optimal solutions generated by exact optimization methods. As a result, decision-makers lack quantitative evidence regarding the solution quality, optimality gap, and computational trade-offs associated with adopting metaheuristic approaches instead of exact solvers.

To address these limitations, this study develops a carbon-constrained, profit-maximizing optimization model for a dual-channel fresh agri-food e-commerce supply chain. The proposed model is solved using GA and PSO through a feasibility-preserving random-key decoding mechanism, and both algorithms are systematically benchmarked against the exact optimal solution to evaluate their solution quality, robustness, and practical applicability.

[Downloaded from ijiepr.iust.ac.ir on 2026-11-06]

Table 1. Comparison of related studies.

Author	Product	Channel	FLW	Carbon	Objective	Solution approach	Case
[10]	Fish	Offline	Yes	Yes	Min cost	Exact MILP	Indonesia
[8]	Fresh fruit	Dual	Yes	Yes	Min cost, emission, waste	Exact MILP	Indonesia
[9]	Dairy	Offline	Yes	Yes	Min cost, emission, waste	Exact MILP	Indonesia
[21]	Agri-food	Offline	Yes	Yes	Min cost	Exact MILP	Indonesia
[7]	Fruits, vegetables	Dual	Yes	Yes, with cap	Max profit	Exact MILP	Indonesia
[19]	Agri-food	Offline	Yes	Yes	Max profit, min emission, waste	Exact MILP	Slovenia
[25]	Plumpy nut	Offline	No	Yes	Min cost	Exact (CPLEX)	India
[22]	Agri-food	Offline	Yes	No	Min cost, max throughput	Exact (CPLEX)	Iran
[23]	Wheat	Offline	Yes	Yes	Min cost, time, impact	Exact (CPLEX)	USA
[13]	Shrimp	Offline	Yes	No	Min cost, waste	Metaheuristics	General
[15]	Saffron	Offline	Yes	No	Min cost, max jobs, quality	Metaheuristics	Iran
[16]	Pistachio	Offline	Yes	No	Min cost	Hybrid metaheuristic	General
[41]	Olive	Offline	Yes	Yes	Min cost	Tabu-based neighbourhood search	Iran
This study	Fruits, vegetables	Dual	Yes	Yes, with cap	Max profit	GA and PSO optimization	Indonesia

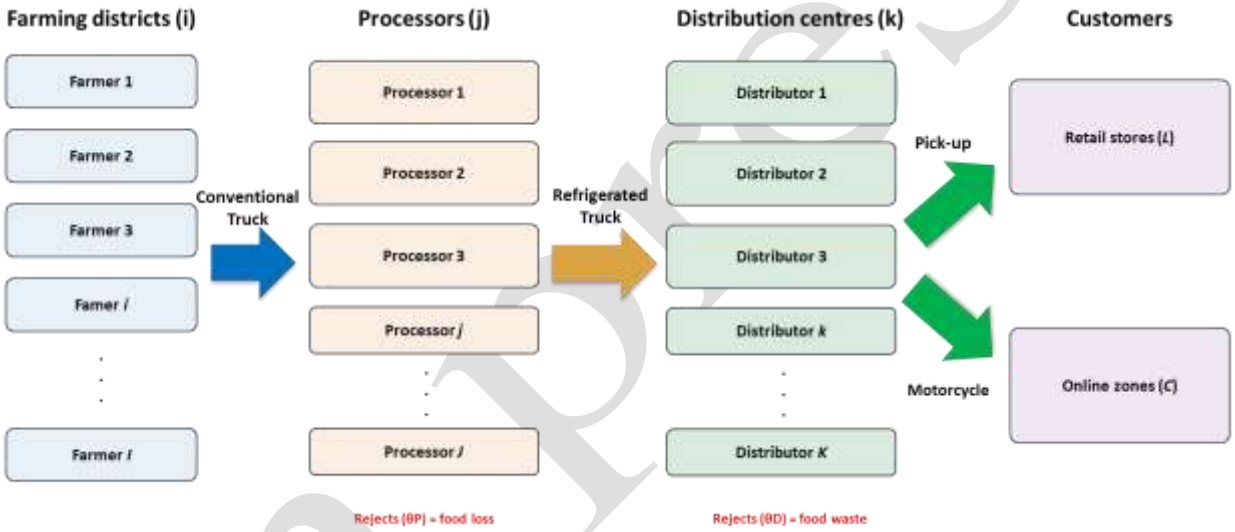


Figure 1. Structure of the fresh agri-food e-commerce network.

3. Problem Description

The proposed fresh agri-food e-commerce network consists of four echelons, as illustrated in Figure 1. Fresh agricultural products, including oranges, avocados, carrots, and tomatoes, are supplied by farmers located in six districts to five processing facilities. At the processing stage, products undergo quality inspection, grading, and packaging before being transported to distribution centers (DCs), each of which is co-located with a processing facility. Upon arrival, products are re-inspected and temporarily stored before being distributed through two sales channels: retail stores served by pickup vehicles and online customer zones served by motorcycles.

The planning problem is formulated over a finite multi-period horizon. In each period, decision-makers determine procurement quantities from individual farmers, production and packaging volumes at processing facilities, shipment allocations to DCs, customer assignments, and demand fulfillment quantities. Customer demand is not required to be fully satisfied, allowing the model to reject economically unattractive or carbon-intensive orders when necessary. In addition, total carbon emissions generated throughout the planning horizon are restricted by a predefined emission cap, while carbon emission costs are incorporated into the objective function.

[Downloaded from ijiepr.iust.ac.ir on 2026-11-06]

4. Assumption and Notation

The proposed optimization model is developed based on the following assumptions:

1. The planning horizon is finite and discretized into equal time periods.
2. Farmer supply capacities, customer demand, and all economic parameters are deterministic and known at the beginning of each planning period.
3. Processing facilities and distribution centers operate under limited production, packing, and cold-storage capacities.
4. Product quality inspection is performed at both processing facilities and distribution centers. A predetermined proportion of products fails inspection, is classified as food waste, and incurs disposal costs.
5. Each retail store and online customer zone is assigned to at most one distribution center in each planning period (single-sourcing policy).
6. Carbon emissions are generated from processing, inspection, cold storage, waste handling, and transportation activities. The cumulative emissions over the planning horizon are constrained by a predefined carbon emission limit.
7. Transportation is performed using trucks, pickup vehicles, and motorcycles, each with fixed vehicle capacities. Transportation costs depend on travel distance and the number of vehicle trips

The following indices and notations are utilized in this article to develop the mathematical model:

Indices

$i \in \{1,2,\ldots,I\}$	Farming districts
$j \in \{1,2,\ldots,J\}$	Processors
$k \in \{1,2,\ldots,K\}$	Distribution centres
$l \in \{1,2,\ldots,L\}$	Retail stores
$c \in \{1,2,\ldots,C\}$	Online customer zones
$g \in \{1,2,\ldots,G\}$	Products
$t \in \{1,2,\ldots,T\}$	Planning periods
$\mathcal{A}_c \subseteq \mathcal{K}$	DCs allowed to serve online c

Decision variables

$x_{ijg\tau}$: Raw quantity of product g bought from district i by processor j in period τ (kg)

$y_{jkg\tau}$: Quantity shipped from processor j to DC k (kg)

$z_{klg\tau}$: Quantity sold by DC k to retail store l (kg)

$w_{kcg\tau}$: Quantity sold by DC k to online zone c (kg)

$H^P_{jg\tau}$, $H^D_{kg\tau}$: Cold-storage inventory at processor j and DC k at the end of period τ (kg)

$u_{jg\tau}$: Quantity packed at processor j (kg)

$\rho^P_{jg\tau}$, $\rho^D_{kg\tau}$: FLW at processor j and DC k (kg)

$n^1_{ij\tau}$, $n^2_{jk\tau}$, $n^3_{kl\tau}$, $n^4_{kc\tau}$: Trips by truck (farm to processor), truck (processor to DC), pick-up and motorcycle (integer)

$b_{kl\tau}$, $b_{kc\tau}$: 1 if DC k serves retail store l or online zone c in period τ, 0 otherwise

E : Total emissions over the horizon (kg CO_2e)

Parameter

$A_{ig\tau}$: Supply available in district i (kg)

$\kappa_{jg\tau}$: Packing capacity of processor j (kg)

$\delta^R_{lg\tau}$, $\delta^O_{cg\tau}$: Demand of retail store l and online zone c (kg)

$\pi^R_{lg\tau}$, $\pi^O_{cg\tau}$: Selling price to retail store l and online zone c (IDR/kg)

$\alpha_{ig\tau}$: Farm-gate price in district i (IDR/kg)

$\beta_{jg\tau}$: Transfer price paid by DCs to processor j (IDR/kg)

$\varphi_{jg\tau}$: Packing cost at processor j (IDR/kg)

$\psi^P_{jg\tau}$, $\psi^D_{kg\tau}$: Inspection cost at processor j and DC k (IDR/kg)

$\eta^P_{jg\tau}$, $\eta^D_{kg\tau}$: Cold-storage cost per kg per period at processor j and DC k (IDR/kg)

$\omega^P_{jg\tau}$, $\omega^D_{kg\tau}$: Waste disposal cost at processor j and DC k (IDR/kg)

$\theta^P_{jg\tau}$, $\theta^D_{kg\tau}$: Fraction rejected at inspection at processor j and DC k

v^1_{ijg}, v^2_{jkg}, v^3_{klg}, v^4_{kcg} : Handling cost per kg on each arc (IDR/kg)

ℓ_{ij}, ℓ_{jk}, ℓ_{kl}, ℓ_{kc} : Road distance on each arc (km)

Q^1, Q^2, Q^3, Q^4 : Capacity of truck, refrigerated truck, pick-up and motorcycle (kg/trip)

p^F : Fuel price (IDR/litre)

f^1, f^2, f^3, f^4 : Fuel use of each vehicle type (litre/km)

ε^{pk} : Emission rate of packing (kg CO_2e/kg)

ε^{iP}, ε^{iD} : Emission rate of inspection at processors and DCs (kg CO_2e/kg)

ε^{sP}, ε^{sD} : Emission rate of cold storage at processors and DCs (kg CO_2e/kg per period)

ε^{wP}, ε^{wD} : Emission rate of waste disposal at processors and DCs (kg CO_2e/kg)

μ : Carbon price (IDR/kg CO_2e)

Γ_τ : Emission cap in period τ (kg CO_2e)

In Press

[Downloaded from ijiepr.iust.ac.ir on 2026-11-06]

e^1, e^2, e^3, e^4 : Transport emission rate of each vehicle type (kg CO2e/kg-km)

S_j^P, S_k^D : Cold-storage capacity of processor j and DC k (kg)

5. Mathematical Model

The model maximises total profit Π, defined as total revenue TR minus seven cost groups: purchasing (C^B), transfer (C^T), packing and inspection (C^O), cold storage (C^S), waste disposal (C^W), logistics (C^L) and carbon (C^E).

$$\textbf{Max } \Pi = TR - C^B - C^T - C^O - C^S - C^W - C^L - C^E \tag{1}$$

$$TR = \sum_{k,l,g,\tau} \pi^R_{lg\tau}\, z_{klg\tau} + \sum_{k,c,g,\tau} \pi^O_{cg\tau}\, w_{kcg\tau} \tag{2}$$

$$C^B = \sum_{i,j,g,\tau} \alpha_{ig\tau}\, x_{ijg\tau} \tag{3}$$

$$C^T = \sum_{j,k,g,\tau} \beta_{jg\tau}\, y_{jkg\tau} \tag{4}$$

$$C^O = \sum_{j,g,\tau} \left(\varphi_{jg\tau}\, u_{jg\tau} + \psi^P_{jg\tau} \sum_i x_{ijg\tau} \right) + \sum_{k,g,\tau} \psi^D_{kg\tau} \sum_j y_{jkg\tau} \tag{5}$$

$$C^S = \sum_{j,g,\tau} \eta^P_{jg\tau}\, H^P_{jg\tau} + \sum_{k,g,\tau} \eta^D_{kg\tau}\, H^D_{kg\tau} \tag{6}$$

$$C^W = \sum_{j,g,\tau} \omega^P_{jg\tau}\, \rho^P_{jg\tau} + \sum_{k,g,\tau} \omega^D_{kg\tau}\, \rho^D_{kg\tau} \tag{7}$$

$$C^L = p^F \sum_\tau \left(f^1 \sum_{i,j} \ell_{ij}\, n^1_{ij\tau} + f^2 \sum_{j,k} \ell_{jk}\, n^2_{jk\tau} + f^3 \sum_{k,l} \ell_{kl}\, n^3_{kl\tau} + f^4 \sum_{k,c} \ell_{kc}\, n^4_{kc\tau} \right) + \sum_{g,\tau} \left(\sum_{i,j} \nu^1_{ijg}\, x_{ijg\tau} + \sum_{j,k} \nu^2_{jkg}\, y_{jkg\tau} + \sum_{k,l} \nu^3_{klg}\, z_{klg\tau} + \sum_{k,c} \nu^4_{kcg}\, w_{kcg\tau} \right) \tag{8}$$

$$C^E = \mu\, E \tag{9}$$

$$E = \sum_{j,g,\tau} \left(\varepsilon^{pk} u_{jg\tau} + \varepsilon^{iP} \sum_i x_{ijg\tau} + \varepsilon^{sP} H^P_{jg\tau} + \varepsilon^{wP} \rho^P_{jg\tau} \right) + \sum_{k,g,\tau} \left(\varepsilon^{iD} \sum_j y_{jkg\tau} + \varepsilon^{sD} H^D_{kg\tau} + \varepsilon^{wD} \rho^D_{kg\tau} \right) + \sum_{g,\tau} \left(\varepsilon^1 \sum_{i,j} \ell_{ij}\, x_{ijg\tau} + \varepsilon^2 \sum_{j,k} \ell_{jk}\, y_{jkg\tau} + \varepsilon^3 \sum_{k,l} \ell_{kl}\, z_{klg\tau} + \varepsilon^4 \sum_{k,c} \ell_{kc}\, w_{kcg\tau} \right) \tag{10}$$

Subject to:

$$\sum_j x_{ijg\tau} \le A_{ig\tau} \qquad \forall i, g, \tau \tag{11}$$

$$\rho^P_{jg\tau} = \theta^P_{jg\tau} \sum_i x_{ijg\tau} \qquad \forall j, g, \tau \tag{12}$$

$$u_{jg\tau} = \left(1 - \theta^P_{jg\tau}\right) \sum_i x_{ijg\tau} \qquad \forall j, g, \tau \tag{13}$$

$$u_{jg\tau} \le \kappa_{jg\tau} \qquad \forall j, g, \tau \tag{14}$$

$$H^P_{jg,\tau-1} + u_{jg\tau} = H^P_{jg\tau} + \sum_k y_{jkg\tau} \qquad \forall j, g, \tau \tag{15}$$

In Press

[Downloaded from ijiepr.iust.ac.ir on 2026-11-06]

$$\rho^D_{kg\tau} = \theta^D_{kg\tau} \sum_j y_{jkg\tau} \qquad \forall k,g,\tau \qquad (16)$$

$$H^D_{kg,\tau-1} + \left(1-\theta^D_{kg\tau}\right)\sum_j y_{jkg\tau} = H^D_{kg\tau} + \sum_l z_{klg\tau} + \sum_c w_{kcg\tau} \qquad \forall k,g,\tau \qquad (17)$$

$$\sum_k z_{klg\tau} \le \delta^R_{lg\tau} \qquad \forall l,g,\tau \qquad (18)$$

$$\sum_k w_{kcg\tau} \le \delta^O_{cg\tau} \qquad \forall c,g,\tau \qquad (19)$$

$$z_{klg\tau} \le \delta^R_{lg\tau}\, b_{kl\tau} \qquad \forall k,l,g,\tau \qquad (20)$$

$$\sum_k b_{kl\tau} \le 1 \qquad \forall l,\tau \qquad (21)$$

$$w_{kcg\tau} \le \delta^O_{cg\tau}\, b_{kc\tau} \qquad \forall k,c,g,\tau \qquad (22)$$

$$\sum_{k\in\mathcal{A}_c} b_{kc\tau} \le 1 \qquad \forall k \notin \mathcal{A}_c \qquad (23)$$

$$b_{kc\tau} = 0 \qquad \forall k \notin \mathcal{A}_c \qquad (24)$$

$$\sum_g H^P_{jg\tau} \le S^P_j \qquad \forall j,\tau \qquad (25)$$

$$\sum_g H^D_{kg\tau} \le S^D_k \qquad \forall k,\tau \qquad (26)$$

$$E \le \sum_\tau \Gamma_\tau \qquad (27)$$

$$\sum_g x_{ijg\tau} \le Q^1 n^1_{ij\tau}, \quad \sum_g y_{jkg\tau} \le Q^2 n^2_{jk\tau} \qquad \forall i,j,k,\tau \qquad (28)$$

$$\sum_g z_{klg\tau} \le Q^3 n^3_{kl\tau}, \quad \sum_g w_{kcg\tau} \le Q^4 n^4_{kc\tau} \qquad \forall k,l,c,\tau \qquad (29)$$

$$x,y,z,w,u,\rho^P,\rho^D,H^P,H^D \ge 0; \quad H^P_{jg0} = H^D_{kg0} = 0 \qquad (30)$$

$$n^1,n^2,n^3,n^4 \in \mathbb{Z}_{\ge 0}; \quad b_{kl\tau}, b_{kc\tau} \in \{0,1\} \qquad (31)$$

Equations (2-5) represent the inventory balance of raw fresh fruits from farmer f and supplied to processor n and distributor d. Equations (6-9) represent the inventory balance of products from distributor d and sold to customers (r,m) according to demand in period t. Equations (10-11) mean the inventory levels are no more than the storage capacities. Equation (12) implies that the total emission of processors, distributors, transport, during the planning period is less than or equal to the allocated carbon cap. Equations (13-16) ensure that the total quantity delivered to customers is not more than truck capacities. Finally, Equation (17) represents the domain of the decision variables.

Equation (1) states the objective, and Equations (2) to (10) define its terms. Constraint (11) limits purchases to district supply. Constraints (12-13) split each receipt into accepted and rejected quantities at the processor, and Constraint (14) caps packing. Constraints (15) and (17) balance inventory at processors and DCs, and Constraint (16) records rejection at the DC. Constraints (18-19) allow partial service but forbids over-delivery. Constraints (20) to (24) enforce single sourcing, and Constraints (22-24) also bar motorcycle service from distant DCs. Constraints (25-26) limit cold storage. Constraint (27) imposes the emission cap. Constraints (28-29) link shipments to integer trips, and Constraints (30-31) set variable domains.

6. Solution Approach: Genetic Algorithm and Particle Swarm Optimization

Figure 2 summarizes the solution framework. Both algorithms share one solution representation, one decoder and one fitness function. They differ only in how they generate new candidate vectors. This design isolates the effect of the search mechanism, so any performance gap reflects GA and PSO rather than different encodings.

[Downloaded from ijiepr.iust.ac.ir on 2026-11-06]

Figure 2 summarizes the solution framework. Both algorithms share one solution representation, one decoder and one fitness function. They differ only in how they generate new candidate vectors. This design isolates the effect of the search mechanism, so any performance gap reflects GA and PSO rather than different encodings.

6.1 Solution representation

A candidate solution is a vector $\boldsymbol{\chi} \in [0,1)^n$ with three segments:

- **Assignment keys** χ^a, one per customer node and period, of length $(|\mathcal{L}| + |\mathcal{C}|)\,|\mathcal{T}|$. For retail store l the decoder selects DC $\lfloor \chi^a_{l\tau}\,|\mathcal{K}| \rfloor$. For online zone c it selects the corresponding element of $\mathcal{A}_c$. Each node therefore receives exactly one DC per period, which satisfies Constraints (16) and (17).
- **Priority keys** χ^p, one per demand item (node, g, τ), of length $(|\mathcal{L}| + |\mathcal{C}|)\,|\mathcal{G}|\,|\mathcal{T}|$. The decoder serves items in descending order of their keys [47].
- **Shadow carbon gene** χ^s, a single value mapped to a shadow carbon price $\zeta = (\chi^s)^2\,\zeta^{\max}$ with $\zeta^{\max} = 2 \times 10^6$ IDR/kg CO_2e. The square gives finer resolution at low prices.

6.2 Decoding procedure

The decoder turns $\boldsymbol{\chi}$ into a full plan (x, y, z, w, n, b) in four steps.

1. **Ranking.** For each processor, product and period, rank districts by the shadow-priced unit cost $\alpha_{ig\tau} + \psi^P_{jg\tau} + \varphi_{jg\tau}\left(1 - \theta^P_{jg\tau}\right) + \omega^P_{jg\tau}\theta^P_{jg\tau} + \nu^1_{ijg} + (\mu + \zeta)\,e_{ijg\tau}$, where $e_{ijg\tau}$ is the emission per raw kilogram on that arc. For each DC, rank processors by the same logic, adding the cheapest upstream cost.
2. **Item loop.** Visit demand items in priority order. For item (l, g, τ), take its assigned DC k and the gross quantity $\delta^R_{lg\tau}/\left(1 - \theta^D_{kg\tau}\right)$ that DC k must receive.
3. **Greedy sourcing.** Fill the gross quantity from processors and districts in rank order, subject to remaining packing capacity (11) and district supply (9). A supply piece is used only if its shadow-priced margin, $\pi -$ unit cost $-\,(\mu + \zeta) \times$ unit emission, stays positive. This rule mirrors the reduced-cost test of linear programming, with ζ acting as the dual price of the carbon cap.
4. **Cap check.** Compute the item's emissions. If they exceed the remaining carbon budget, scale the item down so that the budget reaches zero. Commit the flows and update capacities, supply and budget.

After all items, the decoder sets trip counts to $n = \lceil \text{load}/Q \rceil$ for every arc, which satisfies Constraints (28-29) with the fewest trips. Rejection quantities follow from Constraints (12-13) and (16). The decoder ships goods in the period they are packed, so inventories stay at zero and Constraints (15), (17) and (25-26) hold. Every decoded plan is therefore feasible. The fitness equals the profit in Equation (1):

$$F(\boldsymbol{\chi}) = \Pi(\boldsymbol{\chi}) - M\max\{0,\ E(\boldsymbol{\chi}) - \sum_{\tau} \Gamma_\tau\} \tag{32}$$

The penalty term, with $M = 5 \times 10^6$ IDR/kg CO_2e, acts only as a safeguard against rounding, following the feasibility-first principle of Deb [49]. In all reported runs, the cap excess never exceeded 10^{-9} kg CO_2e.

6.3 Genetic algorithm

The GA follows the real-coded scheme of Holland [11] and Goldberg [45]:

- **Initialization.** Draw P vectors uniformly from $[0,1)^n$.
- **Selection.** Binary tournament: draw two individuals and keep the fitter one.
- **Crossover.** Simulated binary crossover (SBX) [48] with probability p_c and distribution index $\eta_c = 15$. Each gene crosses with probability 0.5.
- **Mutation.** Polynomial mutation with gene-wise probability p_m and index $\eta_m = 20$. Genes are clipped to $[0,1)$.
- **Elitism.** Copy the two best individuals to the next generation unchanged.
- **Stopping.** Stop after a fixed budget of fitness evaluations.

6.4 Particle swarm optimization

Each particle q has a position $\boldsymbol{\chi}_q$, a velocity $\mathbf{v}_q$, a personal best $\mathbf{p}_q$ and access to the swarm best $\mathbf{g}$ [12]. At iteration t, every particle updates as follows:

$$\mathbf{v}_q^{t+1} = \omega_t \mathbf{v}_q^t + c_1 \mathbf{r}_1 \odot \left(\mathbf{p}_q - \boldsymbol{\chi}_q^t\right) + c_2 \mathbf{r}_2 \odot \left(\mathbf{g} - \boldsymbol{\chi}_q^t\right) \tag{33}$$

$$\boldsymbol{\chi}_q^{t+1} = \boldsymbol{\chi}_q^t + \mathbf{v}_q^{t+1} \tag{34}$$

$$\omega_t = \omega_{\max} - (\omega_{\max} - \omega_{\min})\,t/t_{\max} \tag{35}$$

[Downloaded from ijiepr.iust.ac.ir on 2026-11-06]

Here $\mathbf{r}_1$ and $\mathbf{r}_2$ are uniform random vectors and $\odot$ is element-wise multiplication. The inertia weight falls linearly from $\omega_{\max}$ to $\omega_{\min} = 0.4$ [46]. Velocities are clamped to $[-0.2, 0.2]$. A particle that leaves $[0,1)$ is placed on the boundary, and its velocity component is reversed and halved.

6.5 Parameter tuning

We tuned both algorithms with a Taguchi L9 orthogonal array [50] at three levels of three factors (Table 2). Each of the nine settings ran twice on the Java case with a budget of 10,000 evaluations. We used the larger-the-better signal-to-noise (SN) ratio:

$$SN = -10\log_{10}\left(\frac{1}{R}\sum_{r=1}^{R}\frac{1}{\Pi_r^2}\right) \tag{36}$$

where Π_r is the best profit of replicate r in IDR billion. The level with the highest mean SN was chosen for each factor.

Table 2. Factors and levels for Taguchi tuning.

	Factor	Level 1	Level 2	Level 3
GA	Population size P	30	50	100
GA	Crossover prob. p_c	0.7	0.8	0.9
GA	Mutation probability p_m	0.01	0.03	0.05
PSO	Swarm size	30	50	100
PSO	Acceleration (c_1, c_2)	(1.5, 1.5)	(2.0, 2.0)	(1.5, 2.5)
PSO	Initial inertia $\omega_{\max}$	0.7	0.9	1.0

6.6 Exact benchmark and performance measures

We coded the MILP in Python and solved it with the open-source MILP solver of SciPy 1.18, with a relative optimality gap of 0.01% and a time limit of 300 s. The exact profit Π^* serves as the reference. For each algorithm we ran ten independent replications with different random seeds and a budget of 30,000 fitness evaluations. We report the best, mean and worst profit, the standard deviation, the relative percentage deviation $RPD = 100\,(\Pi^* - \Pi)/\Pi^*$, and the CPU time. We compared the two samples of final profits with the two-sided Mann-Whitney U test at $\alpha = 0.05$, as recommended for comparing stochastic algorithms [51]. All code ran in Python 3.13 with NumPy 2.5 on a Linux machine with two Intel(R) Core (TM) i5-8265U CPU @1.60 GHz and 8.00 GB of RAM.

7. Results and Discussion

7.1 Case study and data description

The proposed model was evaluated using a fresh agri-food e-commerce supply chain located on Java Island, Indonesia, which represents the country's largest production and consumption region for fresh fruits and vegetables. The network consists of six production districts supplying four commodities, oranges, avocados, carrots, and tomatoes, to five processing facilities located in Jakarta, Bandung, Yogyakarta, Malang, and Surabaya. Each processing facility is connected to a co-located distribution center (DC), which serves both retail stores and online customer zones. The customer network comprises eight demand nodes distributed across Jakarta, Bandung, Yogyakarta, and Surabaya, while the planning horizon covers three monthly periods.

The input data used in this study are summarized in Table 3. Supply capacities, customer demand, selling prices, operating costs, product rejection rates, and carbon emission factors were adopted from our previous study [7] and complemented with official statistics from Statistics Indonesia and national food loss reports [5]. To ensure reproducibility, parameter values were randomly generated from uniform distributions within the reported ranges using a fixed random seed. Transportation distances were estimated from road distances between production districts and cities, with additional intra-city distances of 10–15 km. Fuel prices and vehicle fuel consumption were based on prevailing Indonesian market conditions. Motorcycle deliveries were restricted to customer zones located within a maximum service distance of 160 km.

7.2 Parameter tuning

The parameter settings for both metaheuristic algorithms were determined using the Taguchi L9 experimental design. The corresponding main effects are presented in Figure 2. For the GA, population size exhibited the greatest influence on solution quality. Smaller populations produced higher SN ratios, indicating that allocating computational resources to additional generations was more effective than increasing the number of individuals within each generation. Consequently, the optimal GA configuration consisted of $P = 30$, $p_c = 0.9$ and $p_m = 0.03$.

For PSO, the initial inertia weight had the strongest impact on optimization performance. A relatively high initial inertia weight promoted global exploration during the early search process before gradually encouraging convergence toward promising regions of the solution space.

[Downloaded from ijiepr.iust.ac.ir on 2026-11-06]

Table 3. Input data of the Java case grouped by decision area.

Parameter	Symbol	Value or range	Unit
Supply and capacity	$A_{ig\tau}$ (orange / avocado / carrot / tomato)	4,816 to 1,344,833 / 22,741 to 2,952,000 / 1,000 to 6,022,083 / 104,833 to 3,590,875	kg per period
	$\kappa_{jg\tau}$	1,666,666 to 5,000,000	kg per period
	S_j^P / S_k^D	5,000,000 / 4,000,000	kg
Market	$\delta_{lg\tau}^R$ / $\delta_{cg\tau}^O$	420,000 to 750,000 / 3,000 to 100,000	kg per period
	$\pi_{lg\tau}^R$ / $\pi_{cg\tau}^O$	14,000 to 44,000 / 13,000 to 32,000	IDR/kg
Purchasing and operations	$\alpha_{ig\tau}$ / $\beta_{jg\tau}$	5,000 to 15,000 / 1,000 to 3,000	IDR/kg
	$\varphi_{jg\tau}$	250 to 550	IDR/kg
	$\psi_{jg\tau}^P$ / $\psi_{kg\tau}^D$	100 to 700 / 100 to 500	IDR/kg
	$\eta_{jg\tau}^P$ / $\eta_{kg\tau}^D$	450 to 1,500 / 800 to 2,500	IDR/kg per period
Food loss	$\theta_{jg\tau}^P$ / $\theta_{kg\tau}^D$	1.5 to 4.2 / 2.2 to 4.0	%
	$\omega_{jg\tau}^P$ / $\omega_{kg\tau}^D$	100 to 150 / 85 to 340	IDR/kg
Logistics	v^1 / v^2 / v^3 / v^4	0.5 to 1 / 10 to 20 / 10 to 30 / 10 to 40	IDR/kg
	Q^1 / Q^2 / Q^3 / Q^4	7,500 / 7,500 / 2,345 / 120	kg/trip
	p^F	6,800	IDR/litre
	f^1 / f^2 / f^3 / f^4	0.25 / 0.25 / 0.125 / 0.025	litre/km
Carbon	ε^{pk}	0.008	kg CO_2e/kg
	ε^{iP}, ε^{iD}, ε^{sP}, ε^{sD}	0.006 each	kg CO_2e/kg
	ε^{wP}, ε^{wD}	0.005 each	kg CO_2e/kg
	ε^1, ε^2, ε^3 / ε^4	0.0001 / 0.00005	kg CO_2e/kg-km
	μ	2,250	IDR/kg CO_2e
	Γ_τ	200,000 to 500,000	kg CO_2e per period

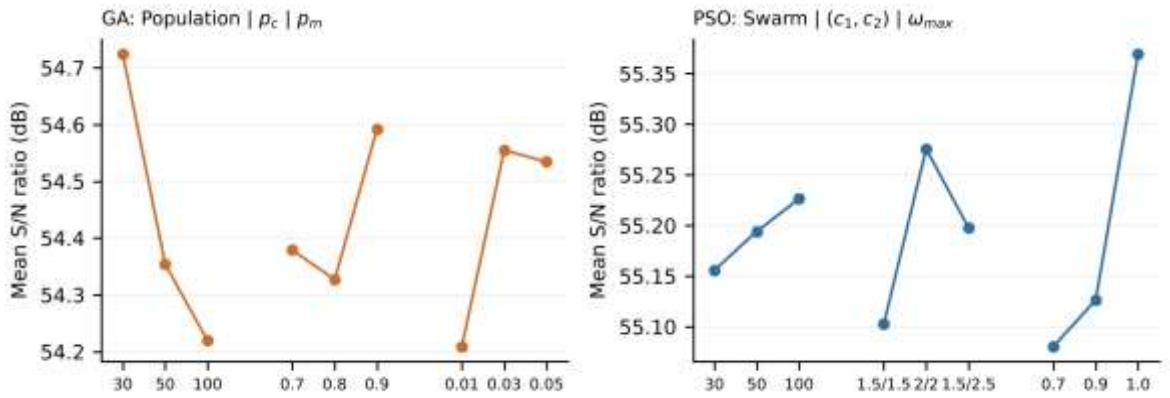


Figure 2. Main effects of the Taguchi L9 experiment on the mean SN ratio

7.3 Comparative performance of GA and PSO

The exact MILP model was solved using the optimizer implemented in Python, obtaining the global optimum within 0.57 s with an optimality tolerance of 0.0004%. The optimal profit reached IDR 608.33 billion. The performance of GA and PSO was subsequently evaluated against this benchmark over ten independent runs, as summarized in Table 4.

Overall, PSO consistently outperformed GA across all evaluation metrics. The best PSO solution achieved IDR 605.67 billion, corresponding to an optimality gap of only 0.44%, whereas the best GA solution produced IDR 576.76 billion, with a gap of 5.19%. Average optimality gaps were 2.55% for PSO and 9.54% for GA. Notably, even the worst PSO solution exceeded the best solution obtained by GA. The superiority of PSO was statistically confirmed using the Mann–Whitney U test (p = 0.0002). Furthermore, PSO demonstrated substantially greater robustness, exhibiting less than half the standard deviation of GA while operating under an identical computational budget of 30,000 objective evaluations.

The convergence behavior of both algorithms is illustrated in Figures 3 and 4. PSO reached 90% and 95% of the exact optimum after approximately 5,300 and 13,200 function evaluations, respectively. In contrast, GA required 27,510 evaluations to reach 90% of the optimum and failed to achieve 95% on average. These results indicate that PSO provides both faster convergence and higher solution quality for the proposed optimization problem.

[Downloaded from ijiepr.iust.ac.ir on 2026-11-06]

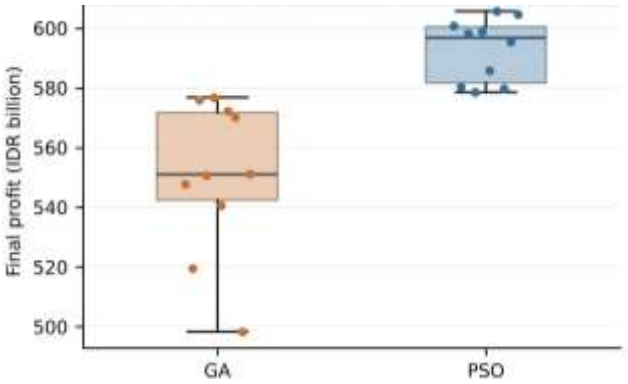


Figure 3. Distribution of final profits over ten runs.

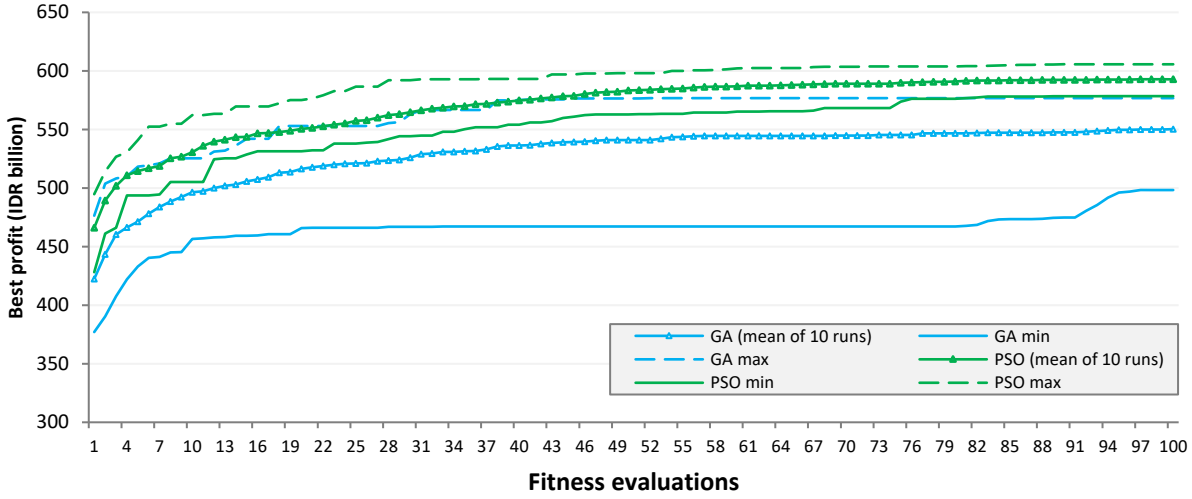


Figure 4. Convergence of GA and PSO (lines show the mean of ten runs; bands show the range).

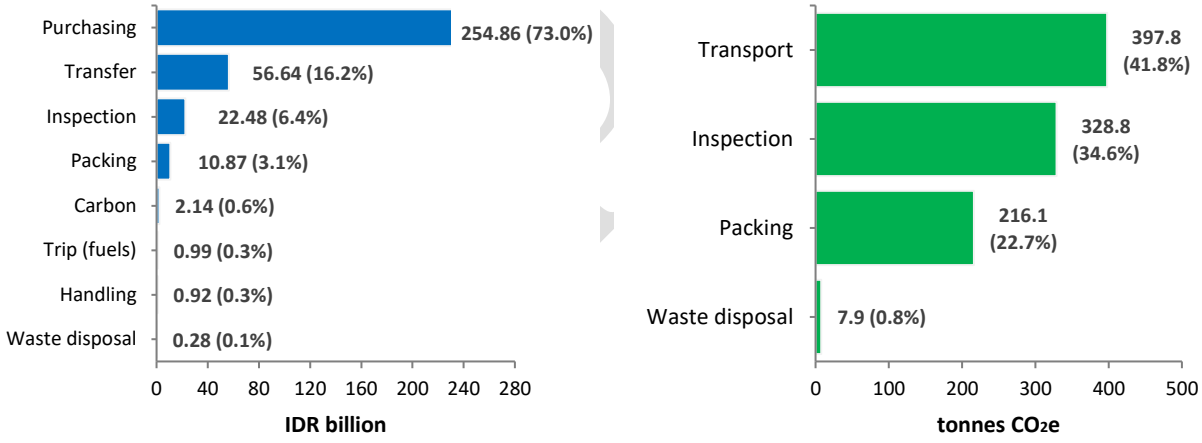


Figure 5. (a) Cost and (b) emission breakdown of the best PSO plan.

Table 4. Profit of GA and PSO over ten runs on the Java case (IDR billion).

Method	Best	Mean	Worst	SD	RPD best (%)	RPD mean (%)	RPD worst (%)	CPU per run (s)
Exact MILP (Python)	608.33				0.00			0.57
GA	576.76	550.31	498.28	25.81	5.19	9.54	18.09	79.8
PSO	605.67	592.80	578.48	10.66	0.44	2.55	4.91	80.4

7.4 Analysis of the optimal agri-food supply chain

The best-performing PSO solution generated a total profit of IDR 605.67 billion. Total revenue reached IDR 954.84 billion, of which 97.9% originated from retail stores and 2.1% from online customers. As illustrated in Figure 5a, procurement represented the dominant cost component, accounting for 73.0% of total operating costs, followed by processor transfer payments (16.2%), quality inspection (6.4%), and packaging (3.1%). Carbon-related costs represented less than 1% of total operating cost.

[Downloaded from ijiepr.iust.ac.ir on 2026-11-06]

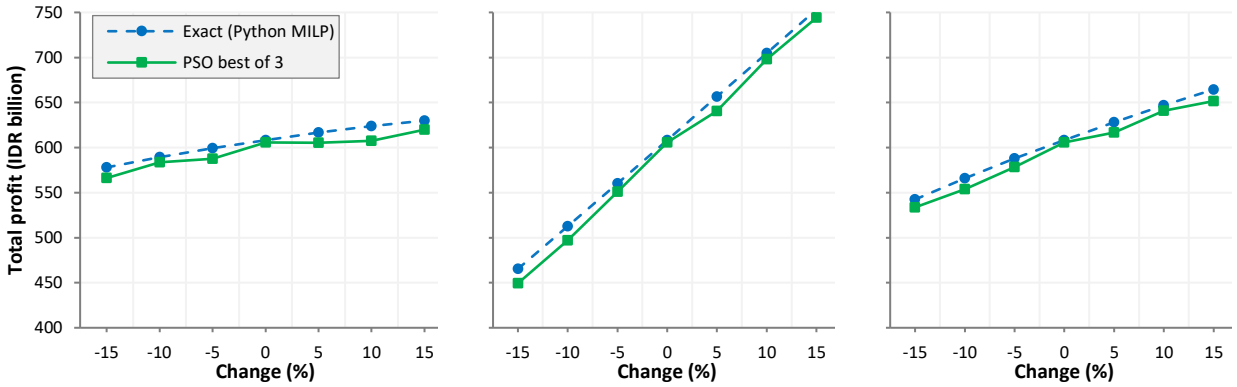


Figure 6. Effect of (a) demand, (b) selling price and (c) emission cap on total profit.

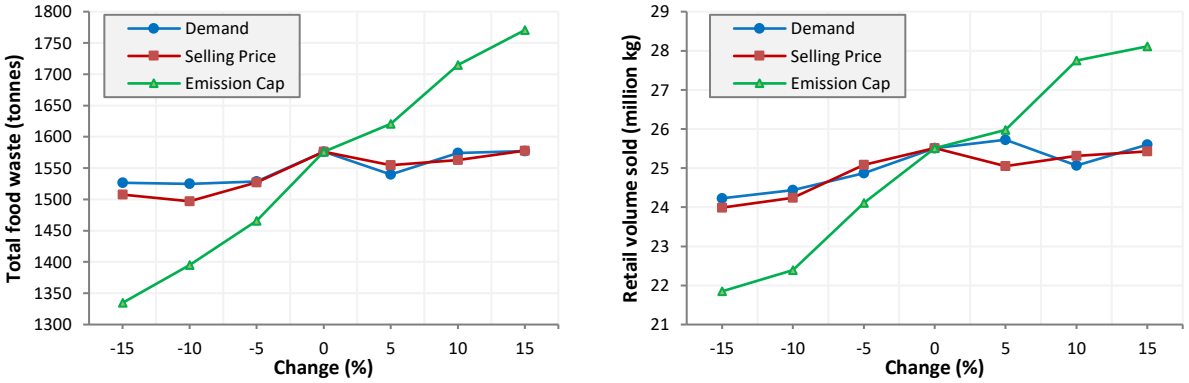


Figure 7. Effect of the three parameters on (a) food waste and (b) retail sales volume in the best PSO plans.

The carbon emission constraint proved to be binding, with total emissions reaching the allowable limit of 950.5 t CO_2e (Figure 5b). Transportation constituted the largest emission source (41.8%), followed by inspection (34.6%) and packaging (22.7%), while waste disposal contributed less than 1% of total emissions. Consequently, the optimization model prioritized geographically closer suppliers, resulting in an average transportation distance of 117 km between farmers and processors.

Because of the binding carbon constraint, only 45.6% of retail demand and 13.7% of online demand were fulfilled. Customer orders with relatively low profit per unit of carbon emission were intentionally rejected, particularly in online channels where additional last-mile transportation increased carbon intensity. Food waste totaled 1.58 million kg, with approximately 52% generated at distribution centers due to higher rejection rates and disposal costs.

7.5 Sensitivity analysis

Sensitivity analysis was conducted by varying customer demand, selling price, and carbon emission limits by ±5%, ±10%, and ±15%. For each scenario, the exact MILP model was solved and compared with three independent PSO runs using 15,000 function evaluations. As shown in Figure 6, PSO closely approximated the exact optimal solutions across all scenarios, producing optimality gaps ranging from 0.91% to 3.42%, with an average deviation of 1.87%.

Selling price exhibited the strongest influence on profitability, with total profit varying between −23.5% and +23.8%. In contrast, changes in the carbon emission cap altered profit by −10.8% to +9.2%, indicating that carbon availability remains a major limiting resource. The estimated marginal value of additional carbon emission allowance was approximately IDR 421,700 per kg CO_2e, closely matching the shadow carbon price identified by PSO, thereby validating the economic consistency of the proposed decoding mechanism. Demand uncertainty had the smallest effect on profitability, changing total profit by less than 5%, since the binding carbon constraint restricted additional throughput regardless of market demand.

[Downloaded from ijiepr.iust.ac.ir on 2026-11-06]

Table 5. Results on larger instances (profit in IDR billion; RPD relative to the exact solution).

Case	Size (I, J, K, L, C, G, T)	Genes	MILP variables (integer)	Exact profit	Exact CPU (s)	GA best (RPD %)	GA mean RPD (%)	PSO best (RPD %)	PSO mean RPD (%)	CPU time (s)
S1 (case)	6, 5, 5, 8, 8, 4, 3	241	2,385 (645)	608.33	0.6	576.76 (5.19)	9.54	605.67 (0.44)	2.55	80
S2	10, 6, 6, 12, 12, 4, 3	361	4,176 (1,152)	680.00	13.8	652.19 (4.09)	4.36	653.94 (3.83)	3.93	40
S3	15, 8, 8, 20, 20, 5, 4	961	13,696 (3,296)	2,224.36	57.5	2,018.12 (9.27)	10.32	2,039.54 (8.31)	9.00	130
S4	20, 10, 10, 25, 25, 6, 6	2,101	37,320 (7,800)	4,446.70	300.0*	3,846.41 (13.50)	14.64	3,862.92 (13.13)	14.85	200

*Time limit reached with a remaining gap of 0.01%. S1 uses 30,000 evaluations and ten runs; S2 and S3 use 10,000 evaluations and S4 uses 6,000, with three runs each.

As illustrated in Figure 7, food waste and retail sales volume increased as the carbon emission cap became less restrictive, reflecting the greater volume of products processed through quality inspection stages. Conversely, variations in demand and selling price produced relatively minor changes in both food waste generation and product throughput, further confirming that carbon availability constitutes the principal operational bottleneck within the proposed supply chain network.

7.6 Scalability

To evaluate the scalability of the proposed algorithms, three larger synthetic problem instances were generated using the same parameter distributions as the base case. Random facility coordinates were assigned within a 900 km × 150 km geographical region, while carbon emission caps were proportionally scaled according to the number of customer nodes. The computational results are summarized in Table 5. The exact MILP model was solved using a maximum computational time of 300 s, whereas GA and PSO employed the tuned parameter settings with 10,000 objective evaluations for instances S2 and S3 and 6,000 evaluations for S4.

The exact optimization approach remained computationally efficient across all problem instances. Solution time increased from 0.57 s for the smallest instance to 57.5 s for S3, while the largest instance (S4) reached the predefined time limit with a remaining optimality gap of only 0.01%. Although the introduction of single-sourcing binary variables increased problem complexity, the linear programming relaxation remained sufficiently tight because transportation vehicles operated with relatively high load utilization.

As problem size increased, the solution quality of both algorithms gradually deteriorated. For PSO, the best relative percentage deviation (RPD) increased from 0.44% for S1 to 3.83%, 8.31%, and 13.13% for S2, S3, and S4, respectively, while GA exhibited a similar trend. This deterioration can primarily be attributed to two factors. First, the chromosome length increased by almost nine times from S1 to S4, substantially enlarging the search space. Second, the computational budget was reduced because each solution evaluation required longer decoding times. Despite this increased complexity, PSO consistently produced higher-quality solutions than GA across all benchmark instances. However, the performance gap between the two algorithms gradually narrowed, and for the largest instance (S4), the average RPD of PSO (14.85%) became slightly higher than that of GA (14.64%).

These findings suggest that exact optimization remains the preferred solution approach for linear carbon-constrained supply chain models of moderate size whenever commercial or open-source solvers are available. Nevertheless, the proposed metaheuristic framework provides a practical alternative for large-scale applications or future model extensions involving nonlinear objective functions and constraints, where exact optimization may become computationally prohibitive.

7.7 Comparison with Previous Studies

The computational results are generally consistent with previous studies on fresh agri-food supply chain optimization while also revealing several important differences. Procurement remained the dominant cost component, accounting for 73.0% of total operating costs. This observation is consistent with our previous MILP study of the same supply chain, where procurement represented 67.4% of total costs [7], as well as with optimization studies on dairy and fish supply chains [9,17].

[Downloaded from ijiepr.iust.ac.ir on 2026-11-06]

However, the proposed carbon-constrained optimization model produced substantially different environmental outcomes. Transportation accounted for 41.8% of total carbon emissions, compared with approximately 87% reported in the previous exact optimization model [7]. This reduction is primarily attributable to the binding carbon emission constraint, which encouraged the optimization model to prioritize geographically proximate suppliers, reducing the average transportation distance to 117 km while simultaneously rejecting long-distance customer orders with relatively low economic returns. Likewise, food waste generated at distribution centers represented 51.9% of total waste, substantially lower than the 96% reported previously [7]. Unlike the earlier model, the proposed formulation does not enforce mandatory procurement or inventory carry-over between planning periods, resulting in food waste originating solely from quality inspection activities across both processing facilities and distribution centers.

From an algorithmic perspective, the proposed PSO consistently outperformed GA when combined with the priority-based random-key encoding scheme. This finding agrees with previous studies demonstrating the superior convergence characteristics of swarm-based optimization methods for complex agricultural supply chain problems [42]. More importantly, unlike most existing metaheuristic studies in agri-food supply chain optimization [13–16], this research systematically benchmarked both algorithms against a certified exact optimum. The best PSO solution achieved an optimality gap of only 0.44%, providing quantitative evidence that an appropriately designed decoding mechanism enables population-based metaheuristics to closely approximate globally optimal solutions for real-world carbon-constrained fresh agri-food supply chain planning problems.

8. Managerial Insight

The findings of this study provide several practical implications for managers operating fresh agri-food e-commerce supply chains under carbon emission constraints.

First, carbon emission allowances should be regarded as a strategic operational resource rather than merely an environmental compliance requirement. The estimated marginal value of approximately IDR 420,000 per kg CO_2e is substantially higher than the prevailing carbon price, indicating that procurement, sourcing, and distribution decisions should prioritize profit generated per unit of carbon emitted. When additional emission allowances or carbon offsets are available below this threshold, acquiring them may improve overall profitability; (ii) supplier selection should emphasize geographical proximity to processing facilities. Transportation remained the largest contributor to total carbon emissions despite optimization. Procuring products from nearby production areas can significantly reduce transport-related emissions while preserving the available carbon budget for revenue-generating activities; (iii) pricing strategies should receive greater managerial attention than demand expansion under carbon-constrained operations. The sensitivity analysis demonstrated that profit was considerably more responsive to selling price than to demand fluctuations. Consequently, optimizing pricing policies and product portfolios offers greater economic benefits than simply pursuing higher sales volumes; (iv) expansion of online distribution channels should be accompanied by low-carbon last-mile delivery strategies. Because online deliveries generate relatively higher transportation emissions while providing lower profit margins, investments in electric motorcycles, route consolidation, or alternative delivery concepts can improve the environmental and economic performance of e-commerce operations; and (v) PSO represents an effective decision-support alternative when exact optimization software is unavailable. The proposed PSO framework achieved solutions within 0.44% of the exact optimum for the real-world case study while relying solely on open-source implementation. However, for larger planning problems, computational budgets should be increased, or hybrid optimization strategies should be considered to maintain solution quality.

9. Conclusions

This study investigated the performance of GA and PSO for solving a carbon-constrained profit maximization problem in a fresh agri-food e-commerce supply chain. A MILP model was extended by incorporating single-sourcing decisions and a planning-horizon carbon emission constraint. To solve the optimization problem using metaheuristics, a feasibility-preserving random-key decoder with a shadow carbon price gene was developed and embedded within both GA and PSO.

[Downloaded from ijiepr.iust.ac.ir on 2026-11-06]

From a methodological perspective, this research contributes to the literature in three important ways. First, it demonstrates that a feasibility-preserving random-key decoder incorporating a shadow carbon price gene enables population-based metaheuristics to closely approximate exact optimization results for carbon-constrained supply chain planning. Second, it provides one of the first systematic benchmark comparisons between GA and PSO against a certified exact optimum for a dual-channel fresh agri-food e-commerce network. Third, it quantifies the economic value of carbon emission allowances, offering new insights into carbon-constrained operational decision-making within Indonesian agri-food supply chains.

Several limitations should be acknowledged. The computational experiments were conducted using deterministic parameter values generated from published data ranges rather than firm-level operational records. The proposed decoder assumes that products are distributed within the same planning period in which they are processed, thereby excluding inventory carry-over decisions. Furthermore, the proposed optimization framework considers only economic objectives and carbon emissions, without explicitly incorporating broader sustainability dimensions such as farmer welfare, employment generation, or social equity.

Future research may extend the proposed framework in several directions. First, stochastic or fuzzy representations of demand and supply uncertainty could improve the realism of operational planning. Second, incorporating temperature-dependent product deterioration, price-responsive demand, and other nonlinear relationships would provide a more comprehensive representation of fresh agri-food supply chains while further demonstrating the advantages of metaheuristic optimization. Third, hybrid optimization frameworks combining PSO with exact optimization techniques could improve both computational efficiency and solution quality. Finally, multi-objective formulations using algorithms such as NSGA-II or MOPSO could be developed to explicitly analyze trade-offs among profitability, carbon emissions, and food waste.

References

[1] Food and Agriculture Organization of the United Nations. (2019). *The State of Food and Agriculture 2019: Moving Forward on Food Loss and Waste Reduction*. Rome: FAO. https://www.fao.org/3/ca6030en/ca6030en.pdf

[2] Gustavsson, J., Cederberg, C., Sonesson, U., van Otterdijk, R., & Meybeck, A. (2011). *Global Food Losses and Food Waste: Extent, Causes and Prevention*. Rome: FAO. https://www.fao.org/4/mb060e/mb060e00.pdf

[3] United Nations Environment Programme. (2021). *Food Waste Index Report 2021*. Nairobi: UNEP. https://www.unep.org/resources/report/unep-food-waste-index-report-2021

[4] Naurah, N. (2022). Food Waste Index 2021: Indonesia jadi penghasil sampah makanan terbesar se-ASEAN. *GoodStats*. https://goodstats.id/article/food-waste-index-2021-indonesia-jadi-penghasil-sampah-makanan-terbesar-se-asean-7FgZ2

[5] Bappenas. (2021). *Laporan Kajian Food Loss and Waste di Indonesia dalam Rangka Mendukung Penerapan Ekonomi Sirkular dan Pembangunan Rendah Karbon*. Jakarta: Kementerian PPN/Bappenas. https://lcdi-indonesia.id/wp-content/uploads/2021/06/Report-Kajian-FLW-FINAL-4.pdf

[6] Parfitt, J., Barthel, M., & Macnaughton, S. (2010). Food waste within food supply chains: Quantification and potential for change to 2050. *Philosophical Transactions of the Royal Society B: Biological Sciences*, 365(1554), 3065-3081. https://doi.org/10.1098/rstb.2010.0126

[7] Rizky, N., Kusrini, E., Mansur, A., & Purnomo, M. R. A. (2026). A profit-oriented optimization model for fresh agri-food e-commerce supply chains with carbon emissions and food waste considerations. *Process Integration and Optimization for Sustainability*. https://doi.org/10.1007/s41660-026-00763-4

[8] Wangsa, I. D., Vanany, I., & Siswanto, N. (2023). An optimization model for fresh-food electronic commerce supply chain with carbon emissions and food waste. *Journal of Industrial and Production Engineering*, 40(1), 1-21. https://doi.org/10.1080/21681015.2022.2099473

[9] Vanany, I., Wangsa, I. D., & Jeremi, N. A. (2023). A multi-objective mixed-integer linear model for sustainable dairy supply chain with food waste and environmental pollutants. *Process Integration and Optimization for Sustainability*, 1-18. https://doi.org/10.1007/s41660-023-00382-3

[Downloaded from ijiepr.iust.ac.ir on 2026-11-06]

[10] Purnomo, M. R. A., Wangsa, I. D., Rizky, N., Jauhari, W. A., & Zahria, I. (2022). A multi-echelon fish closed-loop supply chain network problem with carbon emission and traceability. *Expert Systems with Applications*, 210, 118416. https://doi.org/10.1016/j.eswa.2022.118416

[11] Holland, J. H. (1975). *Adaptation in Natural and Artificial Systems*. Ann Arbor: University of Michigan Press.

[12] Kennedy, J., & Eberhart, R. (1995). Particle swarm optimization. In *Proceedings of ICNN'95, International Conference on Neural Networks* (Vol. 4, pp. 1942-1948). IEEE. https://doi.org/10.1109/ICNN.1995.488968

[13] Mosallanezhad, B., Arjomandi, M. A., Hashemi-Amiri, O., Gholian-Jouybari, F., Dibaj, M., Akrami, M., & Hajiaghaei-Keshteli, M. (2023). Metaheuristic optimizers to solve multi-echelon sustainable fresh seafood supply chain network design problem: A case of shrimp products. *Alexandria Engineering Journal*, 68, 491-515. https://doi.org/10.1016/j.aej.2023.01.022

[14] Gholian-Jouybari, F., Hashemi-Amiri, O., Mosallanezhad, B., & Hajiaghaei-Keshteli, M. (2023). Metaheuristic algorithms for a sustainable agri-food supply chain considering marketing practices under uncertainty. *Expert Systems with Applications*, 213, 118880. https://doi.org/10.1016/j.eswa.2022.118880

[15] Sogandi, F., & Shiri, M. (2023). Metaheuristic algorithms for a sustainable saffron supply chain network considering government policies and product quality under uncertainty. *Journal of Computational Design and Engineering*, 10(5), 1892-1929. https://doi.org/10.1093/jcde/qwad079

[16] Rajabi-Kafshgar, A., Gholian-Jouybari, F., Seyedi, I., & Hajiaghaei-Keshteli, M. (2023). Utilizing hybrid metaheuristic approach to design an agricultural closed-loop supply chain network. *Expert Systems with Applications*, 217, 119504. https://doi.org/10.1016/j.eswa.2023.119504

[17] Vanany, I., Wangsa, I. D., Savitri, N. A., Putera, R. R., Cholili, M., Wibawa, B. M., Atmaja, L., & Tseng, M. L. (2024). Social-economic and environment impacts for a fish reverse supply chain: A mixed integer linear optimization approach. *Cleaner Logistics and Supply Chain*, 13, 100189. https://doi.org/10.1016/j.clscn.2024.100189

[18] Mansur, A., Wangsa, I. D., Rizky, N., & Vanany, I. (2025). An efficient blood supply chain network model with multiple echelons for managing outdated products. *Healthcare Analytics*, 7, 100377. https://doi.org/10.1016/j.health.2024.100377

[19] Drofenik, J., Pahor, B., Kravanja, Z., & Novak Pintarič, Z. (2023). Multi-objective scenario optimization of the food supply chain: Slovenian case study. *Computers & Chemical Engineering*, 172, 108197. https://doi.org/10.1016/j.compchemeng.2023.108197

[20] Peña-Orozco, D. L., Gonzalez-Feliu, J., Salazar-Aguirre, L. T., & Arenas-Ruiz, M. A. (2023). Sustainability fruit supply chain design in the context of decentralized smallholders: Modelling framework and sensitivity analysis. *LOGI: Scientific Journal on Transport and Logistics*, 14(1), 43-54. https://doi.org/10.2478/logi-2023-0005

[21] Yuniarti, R., Masudin, I., Rusdiansyah, A., & Handayani, D. I. (2023). Model of multiperiod production-distribution for closed-loop supply chain considering carbon emission and traceability for agri-food products. *International Journal of Industrial Engineering and Operations Management*, 5(3), 240-263. https://doi.org/10.1108/IJIEOM-10-2022-0045

[22] Rahbari, M., Arshadi Khamseh, A., & Mohammadi, M. (2024). A novel robust probabilistic chance constrained programming and strategic analysis for agri-food closed-loop supply chain under pandemic crisis. *Soft Computing*, 28(2), 1179-1214. https://doi.org/10.1007/s00500-023-09156-y

[23] Sharifi, E., Amin, S. H., & Fang, L. (2024). Designing a sustainable, resilient, and responsive wheat supply chain under mixed uncertainty: A multi-objective approach. *Journal of Cleaner Production*, 434, 140076. https://doi.org/10.1016/j.jclepro.2023.140076

[24] Sharifi, E., Fang, L., & Amin, S. H. (2023). A novel two-stage multi-objective optimization model for sustainable soybean supply chain design under uncertainty. *Sustainable Production and Consumption*, 40, 297-317. https://doi.org/10.1016/j.spc.2023.07.006

[Downloaded from ijiepr.iust.ac.ir on 2026-11-06]

[25] Chaurasia, S., Pati, R. K., Padhi, S. S., & Gavirneni, S. (2024). Is localization better than globalization for sustainability? Evidence from the nutraceuticals industry for managing malnutrition in India. *International Journal of Production Economics*, 268, 109106. https://doi.org/10.1016/j.ijpe.2023.109106

[26] Wang, G. (2024). Order assignment and two-stage integrated scheduling in fruit and vegetable supply chains. *Omega*, 124, 103013. https://doi.org/10.1016/j.omega.2023.103013

[27] Gholipour, A., Sadegheih, A., Mostafaeipour, A., & Fakhrzad, M. B. (2024). Designing an optimal multi-objective model for a sustainable closed-loop supply chain: A case study of pomegranate in Iran. *Environment, Development and Sustainability*, 1-35. https://doi.org/10.1007/s10668-022-02868-5

[28] Abad, A. R. K. K., Barzinpour, F., & Pishvaee, M. S. (2023). Toward circular economy for pomegranate fruit supply chain under dynamic uncertainty: A case study. *Computers & Chemical Engineering*, 178, 108362. https://doi.org/10.1016/j.compchemeng.2023.108362

[29] Belamkar, P., Biswas, S., Baidya, A., Majumder, P., & Bera, U. K. (2023). Multi-objective optimization of agro-food supply chain networking problem integrating economic viability and environmental sustainability through type-2 fuzzy-based decision making. *Journal of Cleaner Production*, 421, 138294. https://doi.org/10.1016/j.jclepro.2023.138294

[30] Yousefi-Babadi, A., Bozorgi-Amiri, A., Tavakkoli-Moghaddam, R., & Govindan, K. (2023). Redesign of the sustainable wheat-flour-bread supply chain network under uncertainty: An improved robust optimization. *Transportation Research Part E: Logistics and Transportation Review*, 176, 103215. https://doi.org/10.1016/j.tre.2023.103215

[31] Rong, A., Akkerman, R., & Grunow, M. (2011). An optimization approach for managing fresh food quality throughout the supply chain. *International Journal of Production Economics*, 131(1), 421-429. https://doi.org/10.1016/j.ijpe.2009.11.026

[32] Zanoni, S., & Zavanella, L. (2012). Chilled or frozen? Decision strategies for sustainable food supply chains. *International Journal of Production Economics*, 140(2), 731-736. https://doi.org/10.1016/j.ijpe.2011.04.028

[33] Liu, Y., Ma, D., Hu, J., & Zhang, Z. (2021). Sales mode selection of fresh food supply chain based on blockchain technology under different channel competition. *Computers & Industrial Engineering*, 162, 107730. https://doi.org/10.1016/j.cie.2021.107730

[34] Yuan, H., Zhang, L., Cao, B.-B., & Chen, W. (2024). Optimizing traceability scheme in a fresh product supply chain considering product competition in blockchain era. *Expert Systems with Applications*, 258, 125127. https://doi.org/10.1016/j.eswa.2024.125127

[35] Ghatreh Samani, M. R., & Hosseini-Motlagh, S.-M. (2021). A novel capacity sharing mechanism to collaborative activities in the blood collection process during the COVID-19 outbreak. *Applied Soft Computing*, 112, 107821. https://doi.org/10.1016/j.asoc.2021.107821

[36] Ghatreh Samani, M. R., & Hosseini-Motlagh, S.-M. (2023). Collaborative activities for matching supply and demand in the platelet network. *Expert Systems with Applications*, 231, 120629. https://doi.org/10.1016/j.eswa.2023.120629

[37] Kurniawan, D., Nazhiifah Ulhaq, A., Fadhilah Althofian, A., & Nur Rachman, R. (2024). An aggregated newsvendor model for multi-item perishable inventories with uncertain demand. *International Journal of Industrial Engineering & Production Research*, 35(4), 29-41. http://dx.doi.org/10.22068/ijiepr.35.4.2097

[38] Syarif, M., Jais, I. R. M., Maflahah, I., & Ihsannudin, I. (2025). Risk evaluation in corn supply chain with FMEA approach: Challenges and opportunities for supply efficiency. *International Journal of Industrial Engineering & Production Research*, 36(1), 181-194. http://dx.doi.org/10.22068/ijiepr.36.1.2259

[39] Dargahi Darabad, S., Izadbakhsh, M., Ghannadpour, S. F., Noori, S., & Mahdavi Mazdeh, M. (2024). A new bi-objective green construction model for multi project supply chain management under uncertainty. *International Journal of Industrial Engineering & Production Research*, 35(1), 58-73. http://dx.doi.org/10.22068/ijiepr.35.1.1813

[Downloaded from ijiepr.iust.ac.ir on 2026-11-06]

[40] Gholian-Jouybari, F., Hajiaghaei-Keshteli, M., Bavar, A., Bavar, A., & Mosallanezhad, B. (2023). A design of a circular closed-loop agri-food supply chain network: A case study of the soybean industry. *Journal of Industrial Information Integration*, 36, 100530. https://doi.org/10.1016/j.jii.2023.100530

[41] Seydanlou, P., Sheikhalishahi, M., Tavakkoli-Moghaddam, R., & Fathollahi-Fard, A. M. (2023). A customized multi-neighborhood search algorithm using the tabu list for a sustainable closed-loop supply chain network under uncertainty. *Applied Soft Computing*, 110495. https://doi.org/10.1016/j.asoc.2023.110495

[42] Gharye Mirzaei, M., Gholami, S., Rahmani, D., Goodarzian, F., & Khanchehzarrin, S. (2026). Robust optimization in an agricultural closed-loop supply chain network design with a price and freshness-dependent demand: Hybrid rat with particle swarm optimization algorithm. *Environment, Development and Sustainability*, 28, 8453-8488. https://doi.org/10.1007/s10668-024-05296-9

[43] Shahsavani, I., Goli, A., & Hajiaghaei-Keshteli, M. (2024). A circular economy approach to design a citrus supply chain network. *Annals of Operations Research*, 1-50. https://doi.org/10.1007/s10479-024-05829-5

[44] Tirkolaee, E. B., Goli, A., & Mardani, A. (2023). A novel two-echelon hierarchical location-allocation-routing optimization for green energy-efficient logistics systems. *Annals of Operations Research*, 324(1), 795-823. https://doi.org/10.1007/s10479-021-04363-y

[45] Goldberg, D. E. (1989). *Genetic Algorithms in Search, Optimization and Machine Learning*. Reading, MA: Addison-Wesley

[46] Shi, Y., & Eberhart, R. (1998). A modified particle swarm optimizer. In *Proceedings of the 1998 IEEE International Conference on Evolutionary Computation* (pp. 69-73). IEEE. https://doi.org/10.1109/ICEC.1998.699146

[47] Bean, J. C. (1994). Genetic algorithms and random keys for sequencing and optimization. *ORSA Journal on Computing*, 6(2), 154-160. https://doi.org/10.1287/ijoc.6.2.154

[48] Deb, K., & Agrawal, R. B. (1995). Simulated binary crossover for continuous search space. *Complex Systems*, 9(2), 115-148

[49] Deb, K. (2000). An efficient constraint handling method for genetic algorithms. *Computer Methods in Applied Mechanics and Engineering*, 186(2-4), 311-338. https://doi.org/10.1016/S0045-7825(99)00389-8

[50] Taguchi, G., Chowdhury, S., & Wu, Y. (2005). *Taguchi's Quality Engineering Handbook*. Hoboken, NJ: John Wiley & Sons

[51] Derrac, J., García, S., Molina, D., & Herrera, F. (2011). A practical tutorial on the use of nonparametric statistical tests as a methodology for comparing evolutionary and swarm intelligence algorithms. *Swarm and Evolutionary Computation*, 1(1), 3-18. https://doi.org/10.1016/j.swevo.2011.02.002

In press

[Downloaded from ijiepr.iust.ac.ir on 2026-11-06]

Follow this article at the following site:

xxxxxxxxxxxxxxx
URL: http://ijiepr.iust.ac.ir/article-1-2186-en.html

In press

[Downloaded from ijiepr.iust.ac.ir on 2026-11-06]