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Multi-echelon open location-routing problem with time window and mixed last-mile delivery for optimizing food supply chains

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ABSTRACT

The pandemic experience made online grocery shopping the new normal. The perishable and Fast-Moving Consumer Goods (FMCG) supply chain should be adjusted to extend their distribution capabilities and adapt to the new business environment. This study introduces the Three-Echelon Open Location-Routing Problem with Time Windows (3E-OLRPTW) with simultaneous home delivery and store pickup services for optimizing last-mile delivery operations. A Mixed-Integer Non-Linear Programming (MINLP) formulation and an improved metaheuristic, the Hybrid Genetic Algorithm (HGA), are developed using a customized local search method. The objective is to minimize total operating costs while accounting for the time window and capacity constraints. Numerical experiments are conducted to evaluate the performance of the developed solution method, comparing it with the improved hybrid variants of the Genetic Algorithm (GA), Artificial Bee Colony (ABC), Simulated Annealing (SA), and Imperialist Competitive Algorithm (ICA) algorithms. Statistical tests confirm that the HGA algorithm outperforms the benchmarks in terms of solution quality and convergence.

1. Introduction

The revenue of Fast-Moving Consumer Goods (FMCG) retail e-commerce reached over 15 billion U.S. dollars in 2020 and surpassed 20 billion in 2023 (Zhou et al., 2019). More than half of the grocery stores in the U.S. offered both home delivery and store pickup services in 2023. The growth rate accelerated in 2020 due to the COVID-19 pandemic with the number of grocery delivery and pickup rising from 1.2 billion U.S.D. in August 2019 to 7.2 billion USD in June 2020 in the United States.[1] Reportedly, 85 percent of buyers who received their orders on time would purchase online again compared to only 33 percent who experienced delays (Esper et al., 2003). The last-mile delivery is regarded as one of the most expensive and least efficient business-to-customer (B2C) operations, accounting for up to 75 percent of the total supply chain costs (Aized and Srai, 2014). Demand for online shopping has been experiencing steady growth, with high costs and inconvenient delivery times remaining the major barriers (Giuffrida et al., 2017; Kalinic et al., 2018; Mokhtari-Moghadam et al., 2023, 2025).

Time is essential in the food supply chain as the products deteriorate over time (Chen et al., 2019). Taking fresh meat as an example, the product quality decreases rather quickly, and it continues to decay until consumed. In this situation, the supply chain revenue depends on the condition of the product. Supply chain optimization plays a crucial role in addressing strict timing and inventory limitations (Bala et al., 2017), while cost-effectively satisfying customers (Chen et al., 2009). Major online retailers like Amazon Flex, Uber Eats, and Senpex use optimization problems for planning their logistics operations.

Approaching routing decisions on a sequential basis and isolated from the location and allocation considerations may result in suboptimal solutions (Pourhejazy et al., 2019). Location-Routing Problems (LRP) have been extended to optimize food distribution (Chao et al., 2019; Govindan et al., 2014; Wu et al., 2017), emergency and disaster management (Bozorgi-Amiri and Khorsi, 2016; Veysmoradi et al., 2017), waste management (Ghaderi and Burdett, 2019; Ghezavati and Beigi, 2016), and e-commerce (Zhou et al., 2019, 2016) aimed to address this issue. The Multi-Echelon Open Location Routing Problem (ME-OLRP) is best suited when logistics are outsourced to a third-party logistics (3PL) service provider (Pichka et al., 2018).

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[1] https://www.eia.gov/outlooks/aeo.

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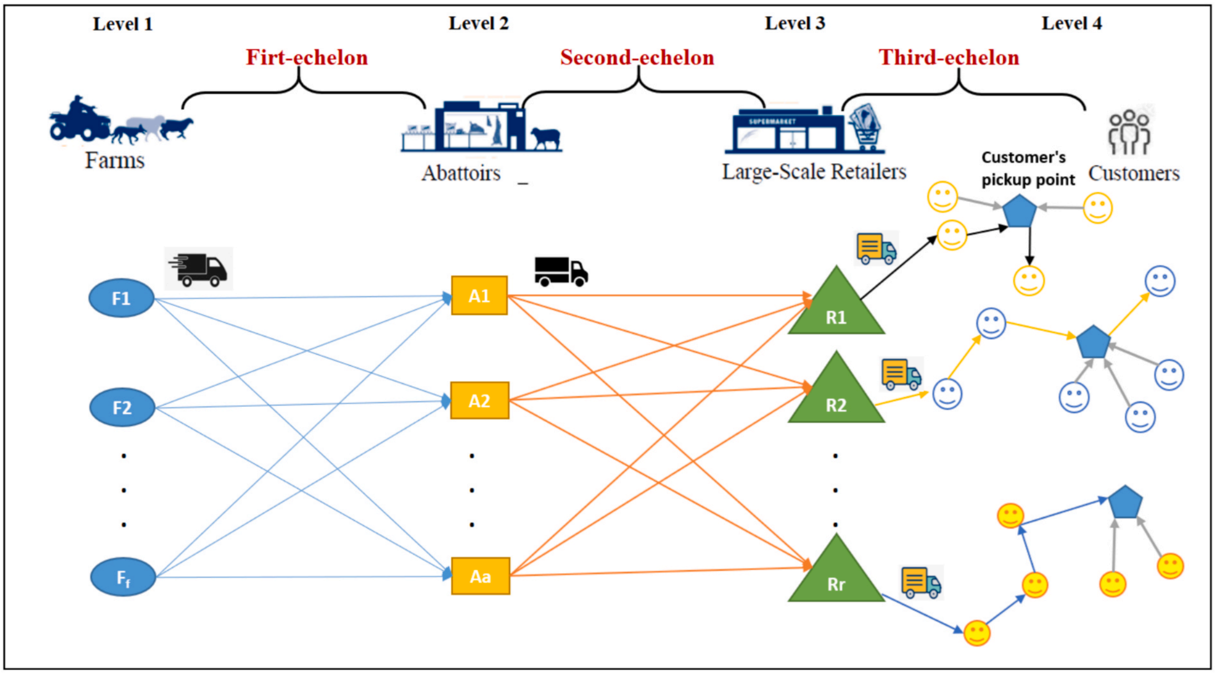


Fig. 1. Illustration of ME-OLRP with Time-Window and Mixed Last-Mile Delivery.

The existing location routing studies did not account for mixed home delivery and store pickup points/local depots. This is perceived as a practical need to extend OLRP for the use case in the online retail of consumer goods and perishables. In the most relevant studies, (Soto-Mendoza et al., 2023) investigated OLRPs for a two-echelon supply system where collection routes for collecting raw materials from local suppliers are allowed. They did not include a time window, three-echelon, and simultaneous home delivery and store pickup options. (Pasha and Mousazadeh, 2024) extended the LRP to allow for the choice of transportation modes, inventory variables, and manufacturing technologies. They did not include routing decision variables, open supply routes, and simultaneous home delivery and store pickup points options. (Rahmanifar et al., 2024), and (Zhou et al., 2024) included both location and routing variables in a single-echelon supply system, did not allow for open supply routes, and simultaneous home delivery and store pickup options. A two-fold contribution is put forward to address the gap.

- A new mathematical formulation is proposed for the Three-Echelon Open Location-Routing Problem with Time Windows (3E-OLRPTW) with simultaneous home delivery and store pickup points/local depots. To the best of the authors' knowledge, OLRP with these specifications has not been studied.
- An advanced solution algorithm is developed for more effective optimization of 3E-OLRPTW with mixed last-mile delivery. The new metaheuristic is equipped with a new local search method, customized evolutionary operators, and a new coding module inspired by scheduling concepts.

The model addresses a real-world situation, where customers place their order online, providing information about the type of product, desired quantity, preferred delivery time window, and the desired delivery service option. The orders should be allocated to the best available third-party facilities for processing. The final products should be assigned to the fleet of vehicles and sent to the customers, considering the stated delivery preferences. The addressed problem is illustrated in Fig. 1. The objective is to minimize the aggregate operational costs, including fixed contracting costs with supply chain partners (i.e., farmers, meat production centers, retailers, the stores, and third-party logistics), processing and transportation, lost-sale, and time window violation costs.

The remainder of this study begins with a review of the relevant literature in Section 2. Section 3 is devoted to problem description and the formulation of the mathematical model. The solution method for solving the optimization problem is presented in Section 4. The numerical results for different operational scales are presented in Section 5 to evaluate the performance of the solution algorithms. Finally, the concluding remarks and suggestions for future research works are provided in Section 6.

2. Literature review

Several studies investigated the optimization of fresh food products using general supply chain network optimization frameworks. (Mohebalizadehgashti et al., 2020) studied a green meat supply chain network in Canada, aiming to minimize total costs and CO_2 emissions from transportation while maximizing facility capacity utilization. (Pasha and Mousazadeh, 2024) extended the model by introducing two new objectives—minimizing delivery time and enhancing resiliency—while incorporating real-world factors such as multi-transportation modes, retailer inventory costs, and multi-manufacturing technologies.

LRPs have been used to optimize supply chains more systematically while addressing location and routing decisions simultaneously to capture interdependencies (Drexl and Schneider, 2015; Nagy and Salhi, 2007; Prodhon and Prins, 2014). Research on LRP is in the growing stage of development (Mara et al., 2021). Capacitated LRP (Bagheri Hosseini et al., 2019; Contardo et al., 2012; Harks et al., 2013; Prins et al., 2007), green LRP (Validi et al., 2020; Wang et al., 2020; Yu et al., 2020), capacitated green LRP (Toro et al., 2017), transportation LRPs (Martínez-Salazar et al., 2014), and LRP considering origin-based cold storage for fresh products (Zhou et al., 2024) are some examples of the developments. Time windows, open routing, and multi-echelon configuration are the required LRP specifications for optimizing the food supply chain when logistics operations are outsourced. The most relevant studies are reviewed below.

Table 1
Review of the most relevant research articles.

Study	Location	Routing	Number of supply echelons	Open route	Time window	Mix delivery & pickup point	e-commerce application	Perishable goods
(Nikbakhsh and Zegordi, 2010)	√	√	2		√			
(Zarandi et al., 2011)	√	√	1		√			
(Fazel Zarandi et al., 2013)	√	√	1		√			
(Wang et al., 2018b)	√	√	2		√			
(Ponboon et al., 2016b)	√	√	1		√			
(Koç et al., 2016)	√	√	1		√			
(Chao et al., 2019)	√	√	1		√			√
(Wang et al., 2018a)	√	√	1		√			√
(Govindan et al., 2014)	√	√	2		√			√
(Wu et al., 2017)	√	√	3		√			√
(Asri et al., 2017)	√	√	1	√	√			
(Bala et al., 2017)	√	√	2		√			√
(Yu and Lin, 2015a)	√	√	1	√	√			√
(Tayebi Araghi et al., 2021)	√	√	1	√				
(Pichka et al., 2018)	√	√	2	√	√			
(Zhou et al., 2016)	√	√	1			√	√	
(Mohebalizadehgashti et al., 2020)	√		3					√
(Pasha and Mousazadeh, 2024)	√		3		√			√
(Soto-Mendoza et al., 2023)	√	√	2	√				√
(Tan et al., 2025)	√	√	2					
(Yıldız et al., 2023)	√	√	2					
(Kusuma et al., 2024)	√	√	2			√		
(Zhou et al., 2024)	√	√	1		√			√
(Rahmanifar et al., 2024)	√	√	1		√			√
This research	√	√	3	√	√	√	√	√

2.1. Location routing problems with time windows for supply chain optimization

Customers are increasingly more cognizant of responsiveness and service quality in their shopping decisions (Govindan et al., 2014). The LRPs with time windows (LRPTW) address this practical need in supply chain optimization. The main objective of this integration is to improve customer service levels and/or address the time constraints mandated by the type of perishable product. The conversion of time windows into budget constraints or cost penalties highlights the economic impacts of this operational consideration (Wang et al., 2018b).

(Jacobsen and Madsen, 1978) introduced the LRPTW and solved the problem with a hard time window to optimize the newspaper distribution in a single-echelon network. (Zarandi et al., 2011) assumed that the times spent between nodes are uncertain and proposed a simulation-based optimization algorithm to solve multi-depot capacitated LRPs. (Fazel Zarandi et al., 2013) extended this study by considering fuzzy time windows for customer demand and developed a chance-constrained programming model for solving it. (Ponboon et al., 2016a) proposed a branch-and-price algorithm to solve the LRPTW. (Ponboon et al., 2016b) investigated the impact of model parameters, such as depot location, depot size, and vehicle size, on LRPTW; they showed that the large depot should be served by large-size vehicles to minimize the overall cost.

(Qazvini et al., 2016) addressed LRPTW with split delivery to improve customer satisfaction and reduce service costs by a reduction in fuel consumption. (Ghezavati and Beigi, 2016) considered penalty cost in the objective function for late arrival time to each node, along with minimizing the maximum time of completion of the collecting return products. (Schiffer and Walther, 2017) explored routing of electric vehicles incorporating the decision of charging stations selection; developing an electric LRPTW with partial recharging, they considered total traveled distance, the total number of vehicles used, and the total number of charging stations as the optimization objectives. (Koç et al., 2016) studied LRPTW with a heterogeneous fleet, aiming to minimize overall supply chain costs.

Considering time window constraints in LRPs has also been studied in the context of perishable goods industries. (Chao et al., 2019) developed a two-stage location–inventory–routing model for optimizing a food distribution network with time windows. They proposed a hybrid heuristic algorithm aiming to minimize the total distribution cost and penalty cost of time window constraint violation. (Wang et al., 2018a) proposed an LRPTW model for fresh food to minimize total logistics costs, including penalty costs of early or late delivery and carbon emission costs. In the most recent study, (Rahmanifar et al., 2024) proposed an LRPSPD with time windows to minimize tardiness and overall delivery costs. Their model addresses pickup and delivery with multiple requests and diverse customer demands, each requiring storage within a specific temperature range and transportation by distinct vehicle types.

2.2. Multi-echelon location-routing problems for supply chain optimization

Supply chains can be best modeled using multi-echelon problems (Drexl and Schneider, 2015). (Nikbakhsh and Zegordi, 2010) addressed a *two-echelon* LRP with soft time windows. They introduced separate time intervals for the delivery of demands to consumers and considered penalty costs for the deliveries that fall into the second time interval. (Darvish et al., 2019) studied flexibility in due date and facility selection in a *two-echelon* LRP; the study revealed that these considerations increase the complexity of the problem, but result in more than 30 percent performance improvement. More recently, (Wang et al., 2018b) formulated a *two-echelon* LRPTW based on a customer clustering model for minimizing overall costs and maximizing customer satisfaction in the context of the beverage industry.

(Govindan et al., 2014) proposed a hybrid metaheuristic to minimize both total cost and environmental impact for perishable food while considering time window constraints for both production and delivery operations in *two-echelon* LRPs. (Wu et al., 2017) studied catering services for high-speed railways and developed a *three-echelon* LRPTW with a time-related budget constraints model with reformulated time deadlines and a hybrid cross-entropy algorithm to optimize the problem. (Bala et al., 2017) developed a *two-echelon* LRPTW model in a newspaper supply context, which aimed to synchronize operations of printing shops and distribution networks, motivated by the lack of inventory. (Wang et al., 2021) explored a *two-echelon* LRPTW with transportation resource sharing, minimizing the number of vehicles and total operational cost simultaneously.

From the most relevant studies, (Yıldız et al., 2023) formulated a mathematical model for the *Two-Echelon* Location-Routing Problem with Simultaneous Pickup and Delivery (2E-LRPSPD) and employed a Branch-and-Cut algorithm to minimize total delivery costs for medium-scale instances. (Kusuma et al., 2024) explored the *2E*-LRPSPD with parcel lockers, minimizing total travel costs. Most recently, (Tan et al., 2025) considered the load carried by trucks as a factor that directly impacts fuel consumption, leading to higher carbon emissions, and attempted to reduce emissions alongside cost and truck usage.

2.3. Open location-routing problems for supply chain optimization

OLRP is suitable for optimizing outsourced activities where the vehicles do not need to return to their origin after completing the tasks, the so-called open tours. This variant received relatively limited attention. OLRP with multi-mode transportation under uncertainty (Veysmoradi et al., 2017), and (Tayebi Araghi et al., 2021) OLRP with stochastic customers' locations are some of the examples. A few articles extended OLRP for multi-echelon optimization. From existing studies, (Pichka et al., 2018) studied 2E-OLRPs, developed two mathematical models for 2E-OLRPs, and employed SA for total logistics cost minimization. (Soto-Mendoza et al., 2023) investigated 2E-OLRPs, incorporating collection routes dedicated to gathering raw materials from local suppliers.

The differences between the developed model in this study and that of the most relevant articles are highlighted in Table 1. Unlike the existing literature on OLRP and LRPTW, our model considers simultaneous home delivery and store pickup points/local depots. Besides, to adapt to the practical needs of e-commerce for fresh products (e.g., red meat supply chains), potential suppliers (farms), processing centers (abattoirs), and large-scale retailers are considered as the facilities in a three-echelon supply chain configuration.

The upcoming section presents a mathematical model for ME-OLRP with time windows and simultaneous home delivery and store pickup services.

3. Mathematical formulation

Supply chain optimization includes variables from three decision layers (Zarandi et al., 2011). Strategic decision variables have a long-term effect and are capital-intensive. Network configuration and facility location planning are prime examples of strategic decisions. Tactical decisions are in place for a relatively shorter period compared to strategic decisions and are less expensive to change/implement. Production and distribution planning decisions belong to the tactical category. Operational decisions are often made regularly and have a short effective period. Although of a different nature, these decisions are interconnected and have a mutual influence. Integrated optimization problems address the underlying interactions between operational, tactical, and strategic decisions (see (Pourhejazy and Kwon, 2016)). This study investigates a new mathematical model that simultaneously addresses location and routing problems under the operating conditions described below.

3.1. Problem description

The multi-echelon distribution network under investigation in the present study comprises livestock suppliers (Farms), production centers (Abattoirs), retail centers, customers and pickup points. The first and second layers are connected by specialized trucks, and because the final product is perishable, large-capacity refrigerated trucks are used to connect the second and third layer facilities. In the retail facilities, orders are consolidated and delivered to the consumer's homes or the designated pickup points, like convenience stores, by small-sized refrigerated trucks. The delivery of Stock Keeping Units (SKU) or final products to the demand points is done by a third-party company, and hence, the vehicles do not need to return to the starting points. Finally, there is a time window associated with every customer order. The problem is hereafter represented by 3E-OLRPTW with mixed last-mile delivery (i.e., home delivery or store pick-up services). Table 2 presents the specifications of the studied supply chain optimization problem.

Table 2
Problem specifications.

Aspects	Settings
Hierarchical Structure	F farms connected to A abattoirs connected to R retailers which supply C customers or pickup points.
Type of Inputs	Prior knowledge of customers' demands over the planning horizon
Solution Method	Hybrid Genetic Algorithm
Objective Function	Minimize aggregated cost including time window violation penalty
Number and type of facilities	Multiple heterogeneous farms, abattoirs, and retailers
Type of Problem	3E-OLRPTW with simultaneous home delivery and store pick-up services

3.2. Model setting and formulation

Let's assume a supply chain network consisting of F farms ($f \in F$), A abattoirs ($a \in A$), R large-scale retailers ($r \in R$), C customers ($c \in C$), and S pickup points ($s \in S$). Farms are connected to abattoirs using either big-size trucks ($V1$) while abattoirs are connected to large-scale retailers utilizing refrigerated trucks ($V2$). The last-mile delivery operations are completed using small-sized refrigerated trucks ($V3$). The model parameters are known in advance except for the demand size ($d \in D$), which is accumulated through an interface application and may vary in different planning horizons. Without loss of generality, the problem is subject to the following assumptions:

- The model is designed for decisions considering one planning horizon.
- Locations of farms, abattoirs, and retailers are known in advance.
- Routing optimization concerns only the last-mile delivery operations and does not account for upstream transportation.
- Abattoirs cannot directly supply final consumers.
- Travel times between different levels are known and deterministic.
- Keeping inventory in facilities is not allowed in the model.
- Each customer can be served by only one of the home delivery or store pick-up options, and their choice of home delivery or store pick-up is known.

The proposed model is formulated as a Mixed-Integer Non-Linear Programming (MINLP) model. The following indices, sets, parameters, and decision variables are used in the mathematical formulation of the problem.

	Symbol	Definition
Indices	$f \in F$	index of farms, where $f = 1, 2, \cdots, n_f$
	$a \in A$	index of abattoirs, where $a = 1, 2, \cdots, n_a$
	$r \in R$	index of retailers, where $r = 1, 2, \cdots, n_r$
	$c \in C$	index of customers, where $c = 1, 2, \cdots, n_c$
	$s \in S$	index of customer pickup points, $s = 1, 2, \cdots, n_s$
	$l \in L$	index of the customer not assigned to pick up points, $l = 1, 2, \cdots, n_l$
	$m \in M$	index of customers who selected store pick-up, $m = 1, 2, \cdots, n_m n_l + n_m = n_c$
	x	the dummy node used to terminate all routes in echelon 3
	$k \in V$	index of vehicle
Parameters	$CAPF_i$	the capacity of facility i, where $i \in \{F, A, R, S\}$
	D_c	customer order size, where $c \in C$

(*continued on next page*)

(*continued*)

	Symbol	Definition
	Fc_i	fixed cost of working with facility i, where $i \in \{F,A,R,S\}$
	Ft_k	fixed cost of working with truck k, where $k \in \{V1,V2,V3\}$
	Vc_i	processing cost of one unit in facility i, where $i \in \{F,A,R,S\}$
	Vt_k	variable cost of transshipment one unit by truck k, where $k \in \{V1,V2,V3\}$
	$CAPT_k$	capacity of truck k, where $k \in \{V1,V2,V3\}$
	PT_{ic}	processing time of order of customer c in facility i, where $i \in \{F,A,R,S\}, c \in C$
	TT_{ijk}	transportation time from node i to node j by truck k
	TC_k	unit transportation cost of truck k, where $k \in \{V1,V2,V3\}$
	W_{kc}	waiting unit cost for delivery to customer c, when truck k arrive early
	$[Et_c, Lt_c]$	boundary of customer time window
	$[et_c, lt_c]$	customer desire time window
	Ept	earliness penalty per time unit
	Lpt	lateness penalty per time unit
	re	earliness penalty increases the rate
	rl	lateness penalty increases the rate
	PU_f	purchasing cost of livestock from farm f
	Sp_c	Sale price to customer c
	COV_{cs}	indicator = 1, if the location of customer c is in the coverage of pickup location s; = 0, otherwise.
Variables	σ_{ic}	Binary variable; = 1, if customer c order is processed in facility $i, i \in \{F,A,R\}$; = 0, otherwise.
	δ_i	Binary variable; = 1, if facility i is selected, $i \in \{F,A,R,S\}$; = 0, otherwise.
	α_{kc}	Binary variable; = 1, if order of customer c is transported by truck k, $k \in \{V1,V2,V3\}$; = 0, otherwise.
	λ_{ijk}	Binary variable; = 1, if truck k travels from i to j, $(i,j) \in \{F, A, R\}, k \in \{V1,V2\}$; = 0, otherwise.
	η_{cs}	Binary variable; = 1, if order of customer c is to be served by pickup point $s, c \in C, s \in S$; = 0, otherwise.
	γ_{ijk}	Binary variable; = 1, if truck k travels from i to j in the third echelon, $(i,j) \in \{R,S,L\}, k \in \{V3\}$; = 0, otherwise.
	β_k	Binary variable; = 1, if truck $k \in \{V3\}$ is used in the third echelon; = 0, otherwise.
	τ_{ic}	Processing start time of order of customer c at facility i, $i \in \{F,A,R\}$
	t_{ic}	Processing finish time of order of customer c at facility i, $i \in \{F,A,R\}$
	u_k	Truck departure time from $i, i \in \{F,A\}$, $k \in \{V1,V2\}$
	ν_k	Truck arrival time at $j, j \in \{F,A\}$, $k \in \{V1,V2\}$
	w_{ki}	Visiting time of node i by truck $k, i \in \{R,S,L\}, k \in \{V3\}$

Considering these notations, the model has been formulated as follows.

$$min(Obj = Z_1 + Z_2 + Z_3 + Z_4) \tag{1}$$

$$Z_1 = \sum_{i \in \{F,A,R,S\}} Fc_i \times \delta_i \tag{2}$$

$$Z_2 = \sum_{c \in C} \sum_{i \in F} PU_i \times D_c \times \delta_i + \sum_{c \in C} \sum_{i \in \{F,A,R,S\}} D_c \times Vc_i \times \sigma_{ic} \tag{3}$$

$$Z_3 = \sum_{k \in V1} \sum_{(i,j) \in (F,A)} (Ft_k + Vt_k \times TT_{ijk}) \times \lambda_{ijk} + \sum_{k \in V2} \sum_{(i,j) \in (A,R)} (Ft_k + Vt_k \times TT_{ijk})$$

$$\times \lambda_{ijk} + \sum_{i \in \{R,S,L\}} \sum_{j \in \{R,S,L\}} \sum_{k \in V3} (Ft_k + Vt_k \times TT_{ijk}) \times \gamma_{ijk} \tag{4}$$

$$Z_4 = \sum_{k \in V3} \sum_{i \in C} \Gamma(w_{ki}) \tag{5}$$

Subject to:

$$\sum_{i \in F} \sigma_{ic} = 1, \forall c \in C \tag{6}$$

$$\sum_{i \in A} \sigma_{ic} = 1, \forall c \in C \tag{7}$$

$$\sum_{i \in R} \sigma_{ic} = 1, \forall c \in C \tag{8}$$

$$\sum_{c \in C} D_c \times \sigma_{ic} \le CAPF_i \times \delta_i, \forall i \in \{F,A,R\} \tag{9}$$

$$\sum_{c \in C} D_c \times \alpha_{kc} \le CAPT_k, \forall k \in \{V1,V2,V3\} \tag{10}$$

$$\lambda_{ijk} \ge \sigma_{ic} + \sigma_{jc} + \alpha_{kc} - 2, \forall k \in V1, \forall c \in C, (i,j) \in (F,A) \tag{11}$$

$$\lambda_{ijk} \ge \sigma_{ic} + \sigma_{jc} + \alpha_{kc} - 2, \forall k \in V2, \forall c \in C, (i,j) \in (A,R) \tag{12}$$

$$\sum_{k \in V1} \alpha_{kc} = 1, \forall c \in C \tag{13}$$

$$\sum_{k \in V2} \alpha_{kc} = 1, \forall c \in C \tag{14}$$

$$\sum_{k \in V3} \alpha_{kc} = 1, \forall c \in C \tag{15}$$

$$\sum_{i \in F} \sum_{j \in A} \lambda_{ijk} \le 1, \forall k \in V1 \tag{16}$$

$$\sum_{i \in A} \sum_{j \in R} \lambda_{ijk} \le 1, \forall k \in V2 \tag{17}$$

$$\tau_{ic} \ge OT_c \forall f \in F, \forall c \in C \tag{18}$$

$$t_{ic} \ge \tau_{ic} + PT_{ic} - M(1 - \sigma_{ic}) \forall i \in \{F,A,R\}, \forall c \in C \tag{19}$$

$$u_k \ge t_{ic} - M(1 - \alpha_{kc}), i \in F, \forall c \in C, \forall k \in V1 or i \in A, \forall c \in C, \forall k \in V2 \tag{20}$$

$$\nu_k \ge u_k + \sum_{i \in F} \sum_{j \in A} TT_{ijk} \lambda_{ijk}, \forall k \in V1 \tag{21}$$

$$\nu_k \ge u_k + \sum_{i \in A} \sum_{j \in R} TT_{ijk} \lambda_{ijk}, \forall k \in V2 \tag{22}$$

$$\tau_{ic} \ge \nu_k - M(1 - \alpha_{kc}), \forall i \in A, \forall c \in C, \forall k \in V1 or \forall i \in R, \forall c \in C, \forall k \in V2 \tag{23}$$

$$\sum_{j \in \{S,L,x\}} \gamma_{ljk} \ge \alpha_{kl}, \forall k \in V3, \forall l \in L \tag{24}$$

$$\sum_{j \in \{S,L,x\}} \gamma_{sjk} \ge \alpha_{km} - M(1 - \eta_{ms}), \forall k \in V3, \forall m \in M, \forall s \in S \tag{25}$$

$$\sum_{i \in \{R,S,L\}} \gamma_{ijk} = \sum_{i \in \{S,L\}} \gamma_{jik}, \forall k \in V3, \forall j \in \{S,L\} \tag{26}$$

$$\sum_{k \in V3} \sum_{j \in \{S,L\}} \gamma_{ijk} \le M \times \delta_i, \forall i \in R \tag{27}$$

$$\sum_{i \in R} \sum_{j \in \{S,L\}} \gamma_{ijk} = \beta_k, \forall k \in V3 \tag{28}$$

$$\sum_{i \in \{S,L\}} \gamma_{ixk} = \beta_k, \forall k \in V3 \tag{29}$$

$$\sum_{c \in C} D_c \times \eta_{cs} \le CAPF_s \times \delta_s, \forall s \in S \tag{30}$$

$$w_{kj} \ge w_{ki} + TT_{ijk} - M\left(1 - \gamma_{ijk}\right), \forall k \in V3, \forall i,j \in \{R,S,L\} \tag{31}$$

$$w_{ki} \ge t_{ic} - M(1 - \alpha_{kc}), \forall k \in V3, \forall i \in R, \forall c \in C \tag{32}$$

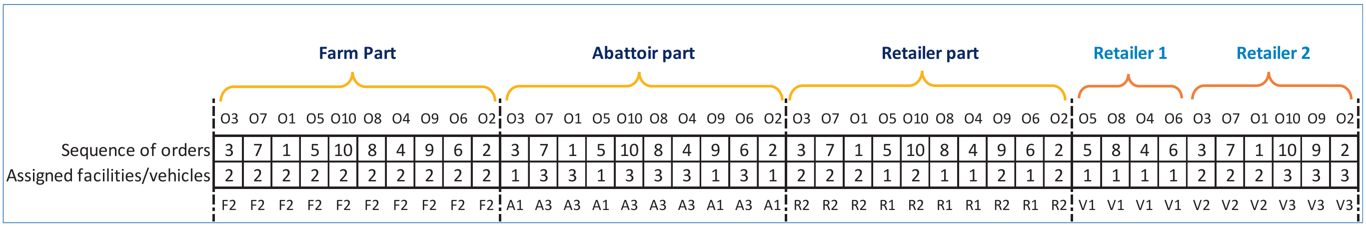


Fig. 2. Chromosome structure.

$$\sum_{j\in\{S,L\}} \gamma_{ijk} \geq \alpha_{kc} + \sigma_{ic} - 1, \forall i \in R, \forall k \in V3, \forall c \in C \tag{33}$$

$$\eta_{cs} \leq COV_{cs}, \forall s \in S, \forall c \in C \tag{34}$$

Objective function (1) minimizes the overall supply chain costs with.

- Equation (2) representing the fixed cost of contracting with third-party network providers;
- Equation (3) calculating the purchasing, preparation, and processing costs;
- Equation (4) showing the transportation cost; and
- Equation (5) demonstrating the time window violation penalty, which is defined as $\Gamma(w_{ki}) = \begin{cases} D_c.(Et_c - w_{ki}).W_{kc}, w_{ki} < Et_c \\ D_c.Ept.(1+re)^{et_c - w_{ki}}, Et_c \leq w_{ki} < et_c \\ 0, et_c \leq w_{ki} < lt_c \\ D_c.Lpt.(1+rl)^{w_{ki}-lt_c}, lt_c \leq w_{ki} < Lt_c \\ D_c.Sp_c, w_{ki} > Lt_c \end{cases}$

Constraints (6)-(8) ensure that every order is processed once at every stage and by one facility. Constraint (9) describes that an order can be processed at the facility only when it is open and the total order processed is below its capacity. Constraint (10) ensures that the order can be transported by truck only and, the truck capacity should be observed. Constraints (11)-(12) guarantee that an order can be transported from A to B if and only if a truck travels from A to B. Constraints (13)-(15) ensure every order is traveled by exactly one truck in every stage. Constraints (16)-(17) guarantee every truck is used once at maximum. Constraint (18) shows that the farm starts processing after the order is received. Constraint (19) calculates the order's finish time at the facility where it is processed.

Constraint (20) represents the truck departure time. Constraints (21)-(22) are formulated to calculate the truck travel time. Constraint (23) defines the order's arrival time at each facility. Constraint (24) ensures that in the third echelon, if an order is selected for home delivery and is assigned to truck k, its location must be visited directly by truck k. Constraint (25) guarantees that every order serviced by a pickup point s is loaded to the truck that travels to s. Constraint (26) established truck flows in the third echelon. Constraint (27) shows that if a retailer is not open, a truck cannot start its journey from this location. Constraint (28) ensures that if a truck is used, it must begin from a retailer, whereas constraint (29) guarantees it finishes at a dummy node.

Constraint (30) ensures the capacity of the pickup point is not violated. Constraint (31) calculates the visiting time of nodes in the third echelon. Constraint (32) calculates the starting time of the truck in the third echelon. Constraint (33) urges the truck to start from a retailer if it carries orders processed at that retailer. Finally, constraint (34) ensures the coverage of the pick-up location is respected. The binary variables receive 0/1 values, while the rest of the variables only accept integer values.

4. Solution method

Vehicle routing problems are categorized as *NP*-hard; the optimization of their extended variant, LRPs, in this study, bears a high computational complexity. This justifies the use of metaheuristics to solve the problem for medium- and large-size instances (Mara et al., 2021; Wang et al., 2018b).

This study proposes to treat the location-routing problem as a machine scheduling problem with due dates to solve ME-OLRPTW. In this approach, farms, abattoirs, and retailers in the first phase are considered parallel machines in a flow shop environment, where jobs (i.e., orders) should go through different processing stages in the same direction. In this definition, traveling times in each echelon correspond to machine setup times. Besides, routing is treated as parallel machine scheduling. The retailers associated with certain customers' orders (jobs) through several vehicles are treated as a sequence of job subsets assigned to a machine for processing. In doing so, the traveling time between locations can be viewed as sequence-dependent setup times in production scheduling, and the service time of each customer (e.g., unloading the items) corresponds to processing times.

As a stochastic search optimization algorithm inspired by Charles Darwin's theory of evolution, Genetic Algorithms (GAs) are among the most used solution methods for solving LRPs (Mara et al., 2021). The computational procedure of GAs begins with encoding the problem into a set of strings (i.e., chromosomes) and continues by applying certain evolutionary operations on the strings, simulating the evolution process (Moghadam et al., 2014). The solution initialization procedure is composed of two phases; in the first phase, a subset of farms, abattoirs, and retailers is selected randomly, and orders are allocated to the active facilities. Notably, for the customers who chose to pick up their items, the orders are allocated (through CP) to the active facilities. In the second phase, routes are planned to accommodate the orders. Additionally, this study improves GA by including a new local search customized for solving the 3E-OLRPTW with mixed deliveries. In the proposed approach, the best-ever found solutions are used as a means of improving the local search procedure. The computational procedure is detailed below.

4.1. Encoding and decoding of solutions

The proposed encoding scheme is a two-segment chromosome with a length of $4 \times (nHD + CP)$. The first segment represents the sequence of orders in each supply chain cycle (farms, abattoirs, retailers, and delivery points), and the second determines the assigned facilities (location-allocation phase) or vehicles (routing phase). Fig. 2 visualizes the structure of the encoded solutions for a small-scale instance with two potential farms (F1, F2), three potential abattoirs (A1, A2, A3), two potential retailers (R1, R2), and eleven customers (C1 C11) two of which opted for a pickup service. The following phases are undertaken to encode a solution.

Phase 1) Location-allocation phase:

- Define open facilities (in this study, farms, abattoirs, and retailers) using three binary strings with the length of n_f, n_a, and n_r, respectively. This ensures that at least one open facility is considered at each stage.
- Sort the orders $nHD + CP$ using random and Length Deviation Tolerance (LDT) methods with an equal probability; apply it separately for every stage.

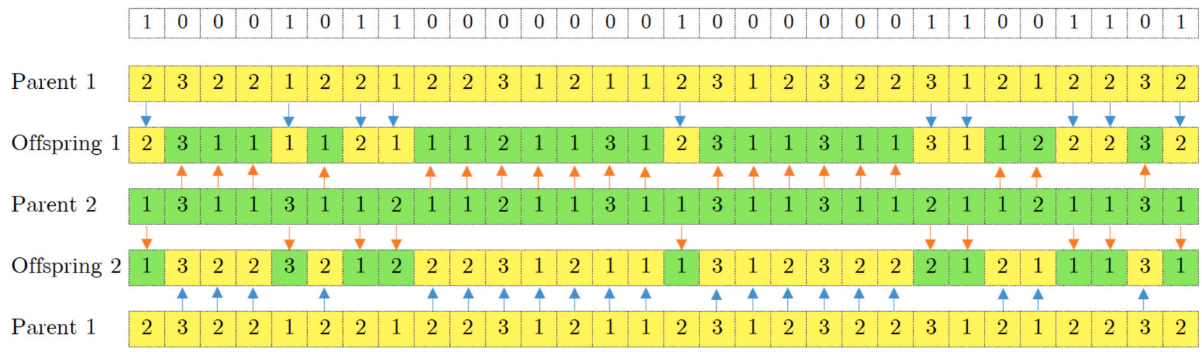


Fig. 3. Uniform crossover for obtaining new solutions.

Table 3
Summary of the case example parameters.

Factors	Levels
Number of orders	A range between 100 and 2000
Number of facilities	3, 5, and 15
Number of customer service points	Number of orders/25
Demand size	U [10,20]
Capacity of customer service points	U [100,200]
Capacity of the first echelon vehicle	10,000
Capacity of the second echelon vehicle	7000
Capacity of the third echelon vehicle	1000
First-echelon vehicle speed	30
Second-echelon vehicle speed	50
Third-echelon vehicle speed	25
Fixed cost of first echelon vehicle	\$100
Fixed cost of second echelon vehicle	\$150
Fixed cost of third-echelon vehicle	\$70
Variable cost of first echelon vehicle	1 \$/min
Variable cost of second echelon vehicle	1.1 \$/min
Variable cost of third-echelon vehicle	0.5 \$/min
Farm third-party contract cost	U [1000, 3000] $\times$ (log $(\frac{\lvert C\rvert}{100}+1))^{0.3}$
Abattoir third-party contract cost	U [2000, 5000] $\times$ (log $(\frac{\lvert C\rvert}{100}+1))^{0.3}$
Retailer third-party contract cost	U [1200, 4000] $\times$ (log $(\frac{\lvert C\rvert}{100}+1))^{0.3}$
Store third-party contract cost	U [100, 200] $\times$ (log $(\frac{\lvert C\rvert}{100}+1))^{0.3}$
Farm processing cost (loading)	U [0.15, 0.3] \$/kg
Abattoir processing cost (unloading + processing + loading)	U [3.5, 7] \$/kg
Retailer processing cost (unloading + loading)	U [0.5, 1.5] \$/kg
Spoilage cost	U [18,25]
Livestock cost	U [2.43, 3.02] \$/kg
The sale price of meat	18 \$/kg
Livestock weight for fulfilling demands	D × 1.3

- Assign the active facilities by random order.

Phase 2) Routing phase.

- Allocate orders to the routes randomly and assign vehicles for every route.

The decoding of the solution is composed of the following steps.

Step 1) Calculate the preparation and processing times of each order, considering the operational parameters of the assigned facility and the order size.

Step 2) Given the orders' position in the sequence, calculate the completion time at each facility using Equation (19).

Step 3) Calculate the vehicles' departure time, which is assumed to be immediately after the ready time of the last order in the batch.

Step 4) Given the vehicle's speed at each echelon, calculate the arrival time of every order.

Step 5) Estimate the number of required vehicles in each echelon.

Step 6) Use Equation (31) to calculate the vehicles' arrival times at the delivery points.

Step 7) Calculate the vehicle's waiting times and the deviation from the desired arrival time.

Step 8) Measure the preparation, processing, transportation, waiting, and time window-violation costs and aggregate them.

4.2. Population initialization and fitness function evaluation

Initial solutions are generated randomly to ensure a diverse population. Each solution is then evaluated considering the overall cost, using Eq. (1). Boltzmann distribution is used to evaluate the fitness values and assign a probability value to every solution P_i, using Equation (35). Since the objective is to minimize overall costs, solutions with a greater fitness value receive a higher priority to be selected for reproduction and survival into the next generation.

$$P_i = \frac{\exp\left(\beta \times \frac{C_i}{C_{worst}}\right)}{\sum_{j\in n_{pop}} \exp\left(\beta \times \frac{C_j}{C_{worst}}\right)}, \forall i \in n_{pop} \quad (35)$$

In this equation, C_i represents the aggregate supply chain cost of solution i; C_{worst} demonstrates the worst cost value; the population number of the algorithm is denoted by n_{pop}, and β is the Boltzmann's constant (the so-called selection pressure). Notably, when $\beta = 0$, all individuals have an equal probability of being selected; otherwise, i.e., when $\beta = \infty$, the probability of selecting an individual with the lowest cost is equal to 1. The β value is, therefore, crucial for the convergence of the solution population to an optimum or near-optimum norm.

4.3. Computational mechanisms

4.3.1. Selection mechanism

Two selection methods are required for reproduction and elitism.

- The Roulette Wheel Selection (RWS) method is used to select individuals for both the crossover and mutation procedures.
- The truncation-based selection mechanism is considered to identify the best solutions from the collective of the old pop_{old} and reproduced solutions, pop_{new}. In this method, individuals are sorted in ascending order of the overall cost, and n_{pop} from the top of the list makes it to the next generation. Similar individuals should be removed before applying the truncation-based selection mechanism. The end of every generation marks the revision of the solution population and reducing the number of individuals to the desired size, pop_{new}.

4.3.2. Crossover mechanism

In the evolutionary phase of the algorithm, at every generation, a uniform crossover mechanism is used to generate new solutions (offspring) from the selected current solutions (parents). For this purpose, (1) two parents are first selected using RWS, and a mask vector (uniform binary vector) with a length equal to the number of facilities ($n_f + n_a + n_r$) is created. (2) The order sequence and facility assignment vectors are sorted, and the respective indices are recorded. (3) Genes in the facility assignment vector are copied from parents to the offspring according to Fig. 3. (4) The recorded indices are considered for obtaining the new order sequence and facility assignment vectors.

4.3.3. Mutation mechanism

The mutation mechanism helps improve population diversity and reduces the chances of premature convergence. This study employs three mutation operators, i.e., swap, conversion, and insertion, to modify the sequence of the orders. For this purpose, an individual is first selected from the population using RWS, followed by applying one of the mutation operators considering an equal probability.

4.3.4. Local search mechanism

A new local search method is developed to improve the exploitation power of the global search algorithm. In this method, the orders are iteratively reassigned across the active facilities to find better alternatives. The pseudocode of the developed local search mechanism is provided below, Algorithm 1.

```
Data: Best solution
Result: Improved solution
initialization;
nOF_l as the number of open facilities at level l;
nVF_l as the number of violated facilities at level l;
forall facilities of level l with capacity violation do
    Find active facilities and calculate the number of assigned orders;
    Sort all facilities of current level based on their capacity;
    if nOF_l = nVF_l = 1 then
        Reassign all of the orders of facility i to facility i + 1;
    else
        if nOF_l > (nVF_l = 1) then
            Reallocate the last orders indices of the over-loaded
              facility to one or multiple active facilities with the
              least deviation;
        end
        if nOF_l = nVF_l ≥ 2 then
            Reassign all of the orders of facility i to facility i + 1;
        end
        if nOF_l > (nVF_l ≥ 2) then
            Reallocate the last orders indices of the over-loaded
              facility to one or multiple active facilities with the
              least deviation;
        end
    end
    Calculate the resulting objective function (OF) value;
    if new OF < current OF then
        Replace the current solution with the new solution;
    end
end
```

Algorithm 1. The iterative local search module.

4.3.5. Termination mechanism

A termination criterion is necessary to halt the solution algorithm's computational procedure. To ensure a fair comparison with benchmark methods, we use maximum CPU time as the stopping criterion, considering instance sizes that range from 500 to 2500 s. Rather than an iteration-based criterion, we adopt CPU time, as it better accommodates the nature of heuristic and *meta*-heuristic algorithms in finding near-optimal or optimal solutions within an acceptable runtime. Additionally, population-based algorithms often require more time per iteration compared to algorithms with strong exploitation power, like SA. Therefore, using CPU time as the stopping criterion ensures a consistent and equitable evaluation across different algorithms.

Table 4
Factor levels for the design of the orthogonal array for HGA calibration.

Parameter	Level		
	1	2	3
nPop	50	80	100
Pc	0.3	0.5	0.7
Pm	0.1	0.3	0.5
SP	2	4	6

5. Numerical results

This section evaluates the performance of the developed algorithm, HGA, comparing it with widely used benchmark algorithms for solving LRPs. For this purpose, the adapted variants of GA (Hiassat et al., 2017), SA (Yu and Lin, 2015b), and ABC (Guo and Zhang, 2017) are considered the baselines. Besides, the hybrid algorithms, GSA (Yu et al., 2022), and ICA + VNS (Tayebi Araghi et al., 2021) are included to ensure a fair comparison. The section continues with a sensitivity analysis and some practical implications of the findings. All algorithms are implemented in MATLAB R2020a and executed on a personal computer with a 2.60 GHz AMD Ryzen 3 CPU and 12 GB of RAM.

5.1. Description of the test instances and the evaluation metrics

Test instances are generated such that the real-world situations are best presented. The parameters and their respective value and ranges are shown in Table 3. Some of the operational parameters are believed to impact the solution algorithm's performance. The demand size, number of facilities on each level, the number of customers, and CP requests are considered in the numerical analysis to capture the possible impact on the algorithms' performance.

In addition to the supply chain cost, which is to be calculated using Equation (1), the percentage of satisfied customers (PSC; Equation (36) is considered to compare the best solutions found by each of the benchmark algorithms. This metric measures the number of demands received at the delivery points within the specified time interval $[et_i; lt_i]$.

$$PSC = \frac{\sum_{i=1}^{n} d_i \times sc_i}{\sum_{i=1}^{n} d_i} \tag{36}$$

In this equation, d_i defines the demand of customer i, and sc_i represents a binary variable equal to 1 if a customer is served within the desired time interval, and 0, otherwise. Relative performance deviation compares the benchmark algorithms against these two metrics.

5.2. Parameter settings

Separate experiments are conducted to calibrate the parameters of each algorithm. For HGA, the population size, selection pressure, crossover, and mutation probabilities are tuned. For GA, the parameters are the same as HGA. The parameters of ABC include the colony size, onlooker size, and maximum trial limit. For SA, the initial temperature (T0), temperature damping rate (alpha), and maximum number of inner iterations (L) are considered. The Taguchi method is used to determine the optimal level of known factors while the effects of uncontrollable factors are minimized. For a full description of how to perform the Taguchi method for tuning the algorithm's parameters, we refer interested readers to (Nabipoor Afruzi et al., 2013).

As a first step, trial-and-error experiments are conducted to determine the initial values for each parameter. Table 4 shows the parameter levels of HGA. Considering the number of known parameters, the respective test levels, and the Taguchi method, an orthogonal array L9 is then designed, which consists of different configurations of parameter levels. To assess which combination of parameter values results in the best algorithm performance, four randomly generated test problems are considered: 3E–OLRPTWH/S P01, 3E–OLRPTWH/S P09,

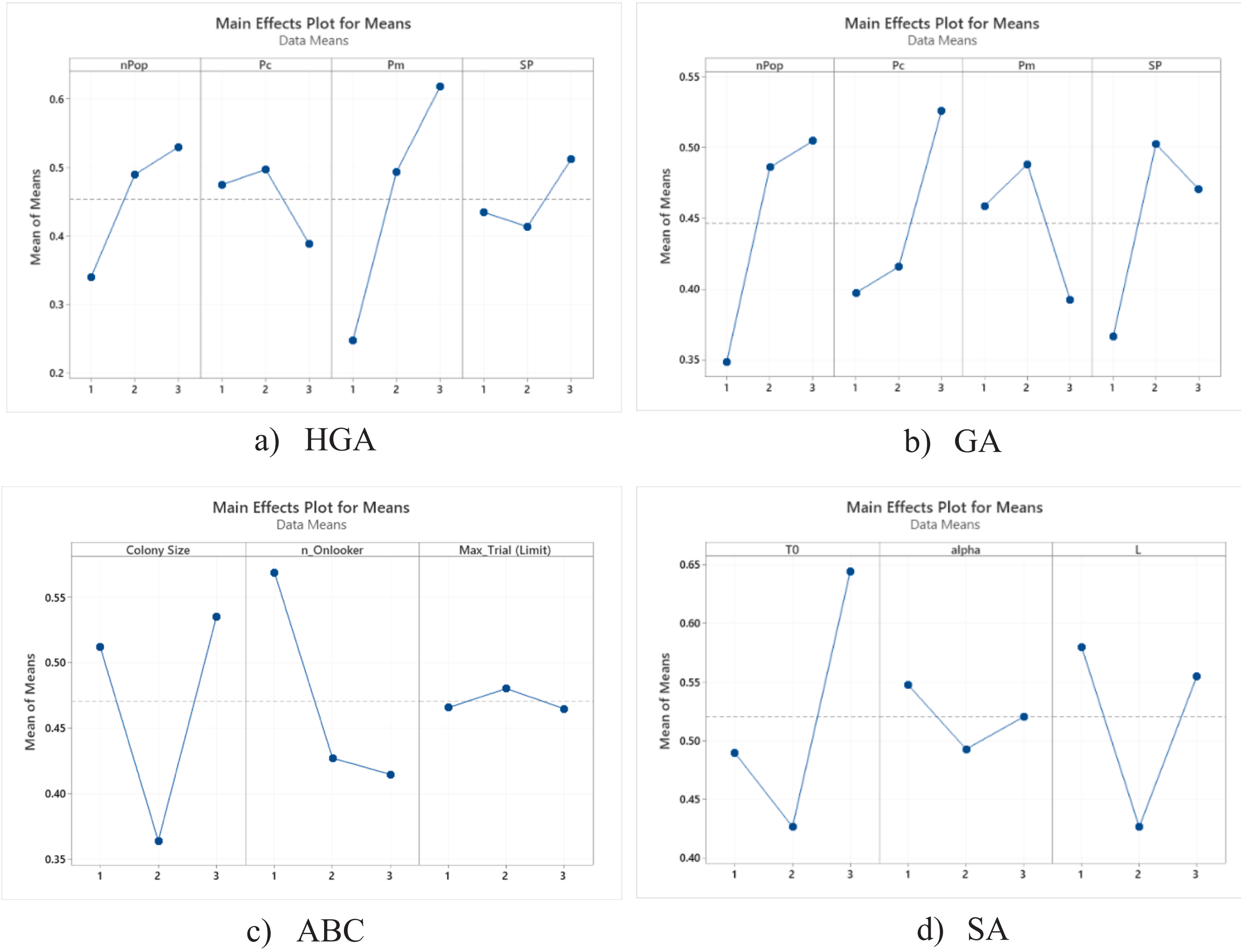


Fig. 4. Mean effects plots for each parameter level in the Taguchi method: (a) HGA, (b) GA, (c) ABC, and (d) SA.

3E–OLRPTWH/S P18, 3E–OLRPTWH/S P27. To ensure the reliability of the outcomes, each problem is solved five times, providing a total of 20 results for each trial.

Next, the performance metrics explained in the previous section are computed and normalized by the Relative Deviation Index (RDI; Equation (37)) for every instance. The RDI values are then calculated for every item of the orthogonal array.

$$RDI_i = \frac{\left|\overline{Pc_i} - Pc_i^{best}\right|}{\left|Pc_i^{max} - Pc_i^{min}\right|} \times 100 \tag{37}$$

In this equation, $\overline{Pc_i}$ refers to the average performance value of the i^{th} experiment, considering 20 runs. Pc_i^{best} represents the best performance value throughout the experiments, while Pc_i^{max} and Pc_i^{min} represent the maximum and minimum values, respectively. It should be noted that $\overline{RDI_i}$ is calculated as the average of RDIs considering four test problems; a measure that is considered as the response value in the Taguchi design approach and the basis of selecting the parameter values for HGA.

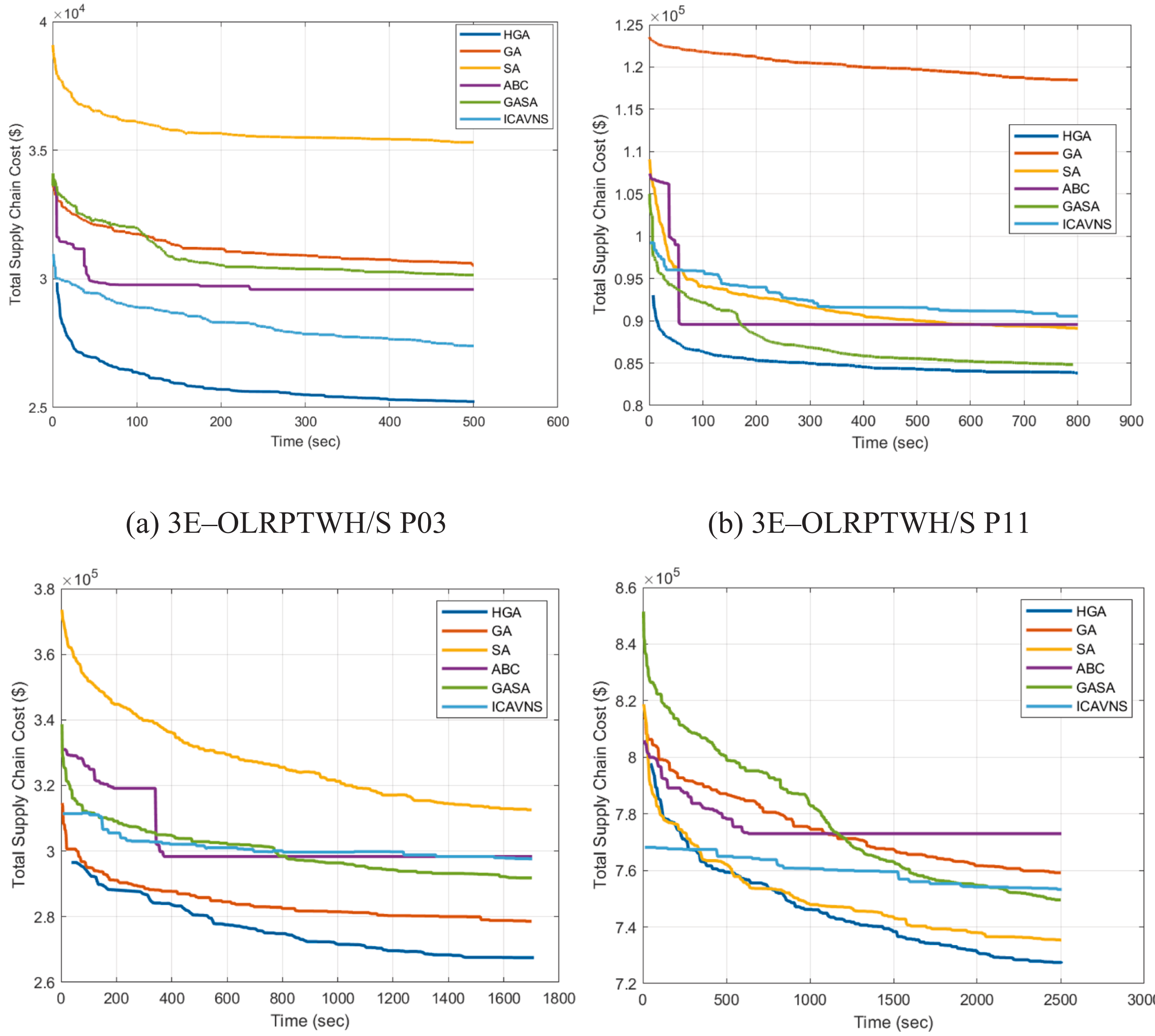
The same procedure is implemented for the parameter setting of GA, ABC, and SA. Besides, the parameters for GSA and ICA + VNS were tuned following (Yu et al., 2022) and (Tayebi Araghi et al., 2021), respectively. The Taguchi experiment results for HGA, GA, ABC, and SA are presented in Fig. 4 (a–d). Table 5 summarizes the optimal parameter values.

Table 5
Parameter setting of HGA, GA, ABC, and SA.

Parameter	HGA	GA	ABC	SA
nPop	100	100		
Pc	0.9	0.3		
Pm	0.2	0.5		
SP	4	2		
Colony Size			80	
n_Onlooker			80	
Max_Trial (Limit)			6	
T0				100
Alpha				0.95
L				50

5.3. Algorithm performance analysis

The performance of HGA is now benchmarked against five other algorithms and considering 33 distinct test instances. The instances are denoted by a 5-field code. For example, an instance with 5 farms, 5 abattoirs, 5 retailers, 40 store points, and 1000 customers is denoted by "5 × 5 × 5 × 40 × 1000". Each algorithm is run three times for each test problem. Fig. 5 shows the algorithms' performance in terms of convergence rate. One can observe that HGA's convergence is steady across problem sizes, and a significantly faster convergence shows its superiority in terms of computational efficiency. In terms of solution quality, algorithms exhibited comparable performance in solving small-scale



(a) 3E–OLRPTWH/S P03

(b) 3E–OLRPTWH/S P11

(c) 3E–OLRPTWH/S P26

(d) 3E–OLRPTWH/S P33

Fig. 5. Fitness value convergence for HGA, GA, ABC, SA, GSA, and ICA + VNS.

instances (P_01–P_09), with only minor gaps between the best-found and average solutions. As the problem size increases, the gap between the best and average solutions across the six competing algorithms becomes more pronounced.

Table 6 summarizes results considering total supply chain cost. In this table, the best-found solution (total supply chain cost), the average cost over three runs, and the standard deviation are reported. The best results from the benchmark tests are highlighted in bold. It can be observed that the majority of the best results are obtained by HGA. Figs. 6 and 7 visualize the best and average costs by the benchmark algorithms, respectively.

Overall, numerical experiments showed that HGA outperforms other algorithms in 26 out of 33 test instances. This superiority is largely attributed to the proposed iterative local search mechanism, which improves the balance between different cost elements in the objective function. Notably, the Adapted SA, which is a single-solution-based local search-based algorithm, achieved superior performance in three test instances, ranking on par with the multi-population-based hybrid ICA + VNS approach.

It is worthwhile to note that HGA has not only yielded the best-found solutions but also demonstrated a more stable performance throughout the experiments. Considering the average solution over three runs, the proposed algorithm demonstrated superiority in 29 out of 33 test configurations, highlighting its consistency in producing high-quality solutions across various attempts. The average solution found by SA is superior in three test cases, while ICA + VNS ranks highest in one instance. Although SA's performance deviates in some test problems, its single-solution-based search mechanism demonstrated relative effectiveness compared to population-based algorithms.

5.4. Statistical analysis

The Wilcoxon signed-rank test is performed considering the best solution obtained by benchmark algorithms to evaluate whether significant differences exist between their performance. The results of the statistical analysis are summarized in Table 7. It is confirmed that the

Table 6
Results considering the overall supply chain cost (best in bold).

Instance No.	HGA			GA (Hiassat et al., 2017)			SA (Yu and Lin, 2015)			ABC (Guo and Zhang, 2017)			GSA (Yu et al., 2022)			ICA + VNS (Tayebi Araghi et al., 2021)		
	Best	Ave	SD	Best	Ave	SD	Best	Ave	SD	Best	Ave	SD	Best	Ave	SD	Best	Ave	SD
P_01	**16 258**	**16 486**	227	16 842	17 161	452	16 445	18 722	3 220	17 931	18 592	581	16 734	16 964	236	16 595	17 374	779
P_02	**19 745**	**19 995**	368	20 054	20 827	1 094	38 748	41 167	3 420	22 639	22 996	460	19 858	21 452	1 702	22 868	23 446	502
P_03	**25 221**	**27 093**	3 159	30 638	31 213	813	32 415	33 862	2 047	28 325	29 207	766	30 153	31 030	763	27 396	30 408	3 097
P_04	33 795	**34 350**	568	38 274	39 159	1 251	39 219	40 059	1 188	36 416	36 961	648	36 951	37 158	182	**33 789**	37 637	3 358
P_05	37 666	**38 792**	1 791	43 221	43 749	747	37 667	44 081	9 070	42 207	42 515	282	38 135	40 463	3 072	**37 097**	40 478	3 054
P_06	38 177	**39 737**	1 914	39 430	40 479	1 482	**36 239**	42 276	8 538	39 753	41 453	2 103	39 895	41 565	1 571	39 600	42 735	3 030
P_07	50 462	53 794	5 495	59 260	59 825	800	**41 138**	**47 434**	8 904	53 833	55 283	1 313	54 732	58 929	4 750	51 104	58 085	6 271
P_08	61 717	64 725	3 187	76 129	77 287	1 637	65 353	65 926	810	64 336	66 647	2 502	64 215	66 790	2 682	**57 917**	**62 478**	5 560
P_09	**67 414**	**74 817**	7 047	69 265	78 852	13 558	76 250	77 237	1 395	77 885	80 419	2 200	74 532	80 406	6 703	76 141	79 737	3 115
P_10	**77 299**	**78 869**	2 401	92 340	92 382	60	80 512	81 748	1 747	93 114	96 274	2 913	83 324	86 586	3 519	84 644	93 242	7 459
P_11	**83 826**	94 456	16 868	118 478	122 696	5 966	89 109	**93 024**	5 536	89 570	95 399	5 161	84 833	103 442	17,695	90 551	100 797	9 841
P_12	**88 862**	98 535	8 516	127 666	132 877	7 369	92 985	**93 447**	654	112 797	117 997	7 752	100 142	109 742	12,132	99 536	114 769	14 912
P_13	**97 336**	**110 700**	19 952	128 782	135 456	9 439	139 291	185 913	65 934	106 989	125 576	20 142	122 417	130 295	7 545	110 945	124 437	14 550
P_14	**97 518**	**118 765**	18 896	132 887	142 228	13 211	121 057	209 425	124 971	144 556	151 037	6 641	100 495	132 428	27 956	123 796	141 245	18 346
P_15	**110 200**	**124 591**	12 828	142 671	151 180	12 034	126 879	200 643	104 317	147 609	154 979	6 624	136 538	143 597	10 619	141 167	154 812	11 817
P_16	134 490	**146 186**	10 959	162 185	163 007	1 161	135 287	232 709	137 775	167 726	172 550	4 640	**133 184**	154 935	18 839	152 923	163 470	9 999
P_17	**122 483**	**133 776**	9 782	164 690	167 423	3 864	136 954	137 364	580	155 444	166 035	9 353	137 372	154 671	15 351	149 675	159 119	8 219
P_18	**155 981**	**165 894**	13 531	173 966	178 275	6 093	161 767	179 737	25 414	198 787	202 499	4 963	164 037	174 448	9 258	188 691	197 470	7 762
P_19	**157 123**	**162 969**	5 965	178 787	183 774	7 053	162 412	171 874	13 380	204 549	204 900	397	180 169	182 703	2 326	185 445	196 005	9 357
P_20	**160 058**	**171 193**	10 450	205 658	208 155	3 532	179 758	292 654	159 659	221 367	224 228	4 720	192 235	197 061	4 879	208 700	216 521	7 206
P_21	**197 738**	**207 655**	14 029	220 831	243 087	31 475	211 523	231 515	28 274	258 425	273 517	18 375	202 498	227 309	24 225	226 922	283 041	48 973
P_22	**205 459**	**225 406**	22 614	273 271	292 970	27 859	212 550	229 781	24 370	282 624	283 728	1 014	212 136	270 843	53 111	225 937	280 009	47 648
P_23	**222 234**	**235 668**	20 832	305 589	306 569	1 385	243 140	245 570	3 437	278 062	296 413	17 362	236 476	255 229	16 242	252 420	295 285	37 150
P_24	233 628	**238 764**	7 384	300 021	311 646	16 441	**224 798**	248 583	33 638	290 163	300 777	15 730	229 502	279 370	44 198	262 751	315 884	46 032
P_25	**243 735**	**257 508**	13 541	322 539	339 544	24 048	290 376	292 913	3 587	334 848	351 631	24 453	277 998	307 736	32 738	298 565	320 927	35 529
P_26	**267 517**	**274 959**	11 274	278 590	316 920	54 207	312 568	420 106	152 082	298 334	319 579	27 265	291 824	298 562	9 925	297 649	345 314	41 283
P_27	**291 209**	**301 397**	14 592	379 642	379 885	343	327 584	330 836	4 600	348 804	365 409	15 682	301 204	353 813	45 562	332 398	379 864	41 321
P_28	**294 558**	**296 503**	2 403	337 047	344 017	9 857	338 228	341 666	4 862	349 911	365 570	17 406	339 156	359 199	18 083	329 128	365 098	35 848
P_29	**319 451**	**323 388**	5 739	337 559	347 035	13 402	339 657	354 293	20 698	361 905	388 943	25 135	371 680	386 680	18 509	355 907	395 808	36 657
P_30	**329 207**	**335 544**	9 187	409 094	410 388	1 831	365 708	373 318	10 762	385 631	394 748	9 001	371 631	385 669	12 157	370 471	405 113	30 808
P_31	**563 185**	**583 119**	18 037	644 036	665 492	30 343	742 575	802 175	84 286	651 796	655 332	5 002	630 109	636 179	5 257	680 769	899 287	191 351
P_32	**625 965**	**631 847**	24 325	661 028	663 821	3 950	818 704	853 814	49 654	705 845	708 514	3 774	645 443	667 172	23 769	689 326	805 074	137 468
P_33	**703 408**	**715 441**	12 197	759 174	770 299	15 733	735 584	787 749	73 773	772 993	785 226	17 300	749 596	758 117	7 379	753 284	899 595	142 959
Sum			330 057			322 492			1 172 584			281 661			462 934			1 021 262

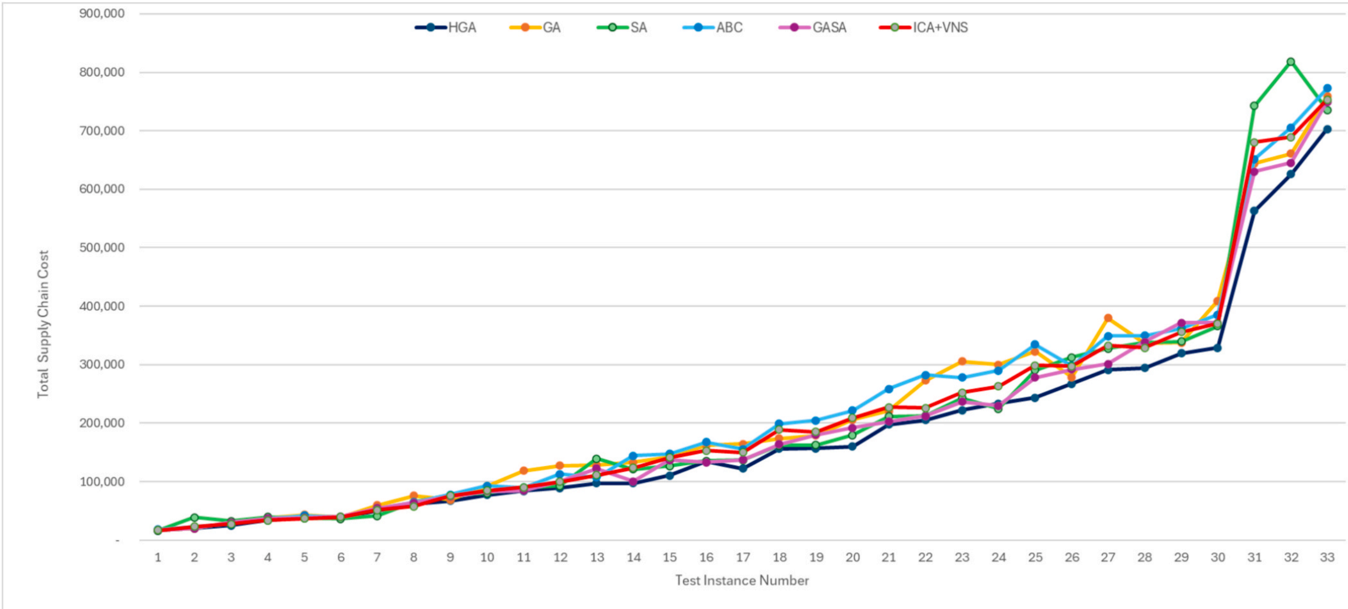


Fig. 6. Illustration of best-found solution amongst competing algorithms.

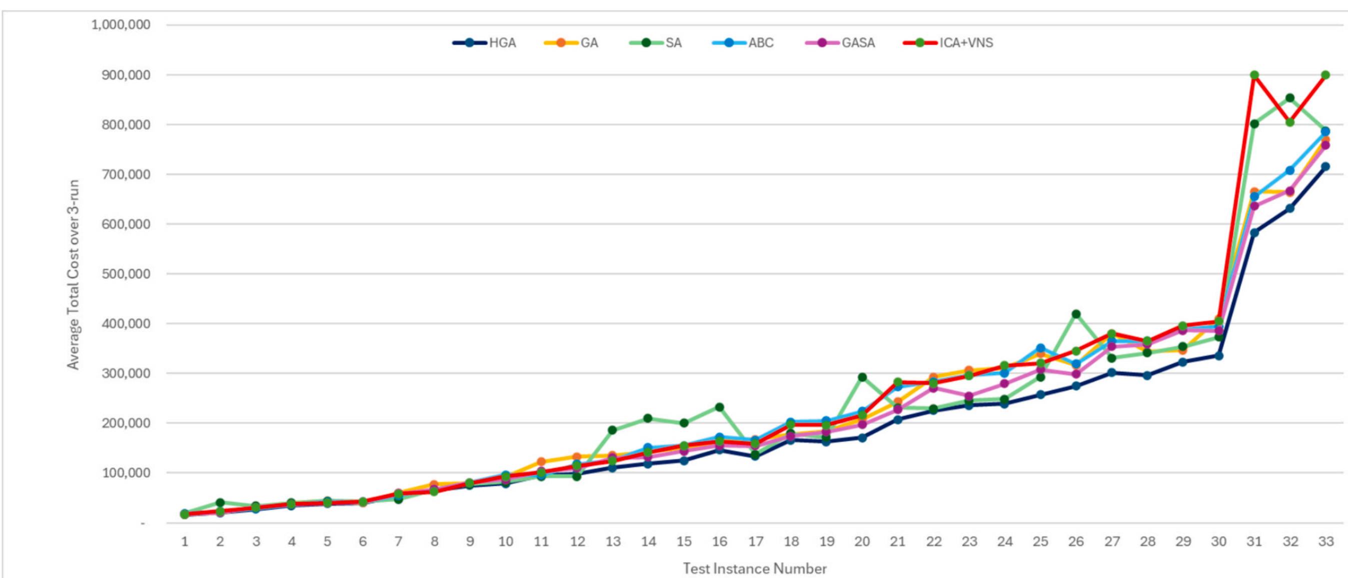


Fig. 7. Illustration of the average solution amongst competing algorithms.

difference in minimum total costs is meaningful. The superiority is believed to be driven by the customized local search, which enhanced the algorithm's exploitation capability.

5.5. Sensitivity analysis and practical implications

The primary objective of the optimization method was to minimize the total supply chain costs, including the penalty costs regulated by the soft time window. As a final step in numerical analysis, customer satisfaction rates are evaluated considering the soft time window to draw practical conclusions. Analyzing the percentage of satisfied customers across different instances showed that the satisfaction percentage reduced with an increase in demand size (see Table 8). Comparing the results from different algorithms in Fig. 8 confirms that increasing the number of pickup points/local depots for the same demand sizes improves customer satisfaction.

Table 7
Comparison of algorithms' performance using Wilcoxon signed-rank test.

		GA	SA	ABC	GSA	ICA + VNS
HGA	p-value	5.39E-07	1.06E-05	5.39E-07	2.10E-06	1.61E-06
	W	0.0	34	0	15	12

This finding is in line with the existing literature where delivery time is regarded as one of the main difficulties in home-delivery operations (Giuffrida et al., 2017; Kalinic et al., 2018, Mokhtari-Moghadam et al., 2023, 2025).

Increasing the number of delivery points is a costly solution to improve customer satisfaction. As an alternative solution, companies extend delivery time slots to accommodate resource constraints as the customer base grows; this leads to reductions in overall logistics costs. Delivery time-window extensions should be approached carefully when the product is perishable and its quality deteriorates over time, as is the case in this study. A sensitivity study is performed to examine how

Table 8
Results considering the percentage of satisfied customers.

No.	Problem size	HGA		GA		SA		ABC		GSA		ICA + VNS	
		Best	Ave	Best	Ave	Best	Ave	Best	Ave	Best	Ave	Best	Ave
P_01	3–3–3-4-100	94,3	88,7	97,9	95,2	98,8	96,7	97,7	92,7	99,2	94,2	95,7	81,6
P_02	3–3–3-6-150	100,0	99,5	100,0	95,9	90,3	89,5	100,0	99,5	100,0	100,0	100,0	99,7
P_03	3–3–3-8-200	99,0	96,3	99,0	98,2	100,0	99,0	98,8	98,8	100,0	98,9	98,5	94,0
P_04	3–3–3-10-250	98,6	96,2	99,7	99,0	100,0	99,3	99,5	97,0	100,0	98,3	98,7	97,2
P_05	3–3–3-11-280	99,7	98,9	99,6	99,2	100,0	99,8	100,0	99,0	100,0	100,0	100,0	98,8
P_06	3–3–3-12-300	99,0	97,3	99,4	99,4	100,0	98,8	99,7	95,6	100,0	99,5	99,6	98,0
P_07	3–3–3-14-350	99,4	98,5	99,6	99,2	100,0	100,0	98,1	97,1	99,8	99,4	99,4	96,8
P_08	3–3–3-16-400	99,4	97,4	99,6	99,5	100,0	99,8	97,0	96,4	100,0	96,6	97,9	95,6
P_09	3–3–3-18-450	100,0	99,6	100,0	100,0	97,5	91,9	100,0	97,2	99,8	97,3	99,3	96,0
P_10	3–3–3-20-500	100,0	100,0	100,0	100,0	100,0	92,3	95,8	94,0	100,0	99,4	98,1	95,2
P_11	5–5–5-22-550	98,0	96,8	98,7	98,5	100,0	100,0	95,8	95,4	99,2	98,5	98,1	95,6
P_12	5–5–5-24-600	99,4	98,8	99,6	99,1	99,6	97,7	97,0	95,8	100,0	98,4	97,9	93,0
P_13	5–5–5-26-650	100,0	98,5	99,7	99,1	55,3	30,5	94,5	93,2	100,0	98,7	94,6	91,0
P_14	5–5–5-28-700	99,0	97,8	99,8	99,1	91,3	45,7	94,7	93,8	99,6	98,3	95,4	91,4
P_15	5–5–5-30-750	99,3	98,4	99,7	99,2	90,2	48,6	91,5	91,2	100,0	99,0	94,2	90,0
P_16	5–5–5-32-800	99,3	97,0	99,3	98,3	95,6	47,8	90,3	89,5	99,3	97,5	93,4	90,7
P_17	5–5–5-34-850	99,0	97,2	99,6	99,4	99,7	97,6	88,4	88,0	99,8	98,2	95,1	90,6
P_18	5–5–5-36-900	93,7	88,2	86,0	84,5	77,4	69,1	82,4	79,8	99,7	94,2	83,8	80,6
P_19	5–5–5-38-950	95,7	91,4	94,5	89,6	77,9	70,0	83,9	83,5	98,9	94,4	85,8	82,5
P_20	5–5–5-40-1000	90,7	87,6	87,3	86,0	73,0	36,5	82,1	80,7	93,9	90,3	84,7	81,2
P_21	10–10–10-42-1050	92,4	88,8	92,3	91,6	85,2	78,9	84,6	83,9	95,3	93,6	86,7	85,1
P_22	10–10–10-44-1100	97,2	91,6	89,6	87,4	88,2	83,2	85,4	84,8	96,2	92,8	88,7	82,8
P_23	10–10–10-46-1150	86,4	85,0	83,5	82,8	82,6	81,2	84,7	83,1	86,4	84,1	82,2	80,1
P_24	10–10–10-48-1200	83,8	83,3	87,9	86,5	80,3	75,8	83,9	83,4	90,6	86,8	85,8	81,6
P_25	10–10–10-50-1250	83,1	80,9	82,5	82,0	74,5	69,4	81,1	80,0	82,3	82,1	81,0	77,4
P_26	10–10–10-52-1300	79,8	79,0	84,7	81,6	51,2	27,5	79,6	78,7	85,1	83,9	83,5	80,2
P_27	10–10–10-54-1350	74,8	73,4	80,3	78,9	67,4	59,3	75,4	73,4	80,3	78,3	78,2	74,1
P_28	10–10–10-56-1400	75,0	71,6	78,9	75,2	61,6	61,1	75,6	74,2	78,3	75,7	76,3	71,7
P_29	10–10–10-58-1450	77,9	75,3	77,8	74,9	69,2	65,2	73,4	71,7	77,9	77,6	77,4	73,5
P_30	10–10–10-60-1500	76,3	71,6	77,1	76,9	66,3	58,5	71,6	68,6	76,2	75,1	76,0	71,1
P_31	15–15–15-68-1700	62,1	55,9	63,3	58,7	68,2	62,9	54,7	53,8	65,0	63,6	74,6	70,1
P_32	15–15–15-74-1850	69,1	63,1	61,0	54,5	70,0	66,8	61,8	56,3	64,0	61,6	67,7	62,4
P_33	15–15–15-80-2000	61,7	57,9	63,4	59,2	57,8	56,9	48,6	47,3	66,1	62,3	64,2	59,1

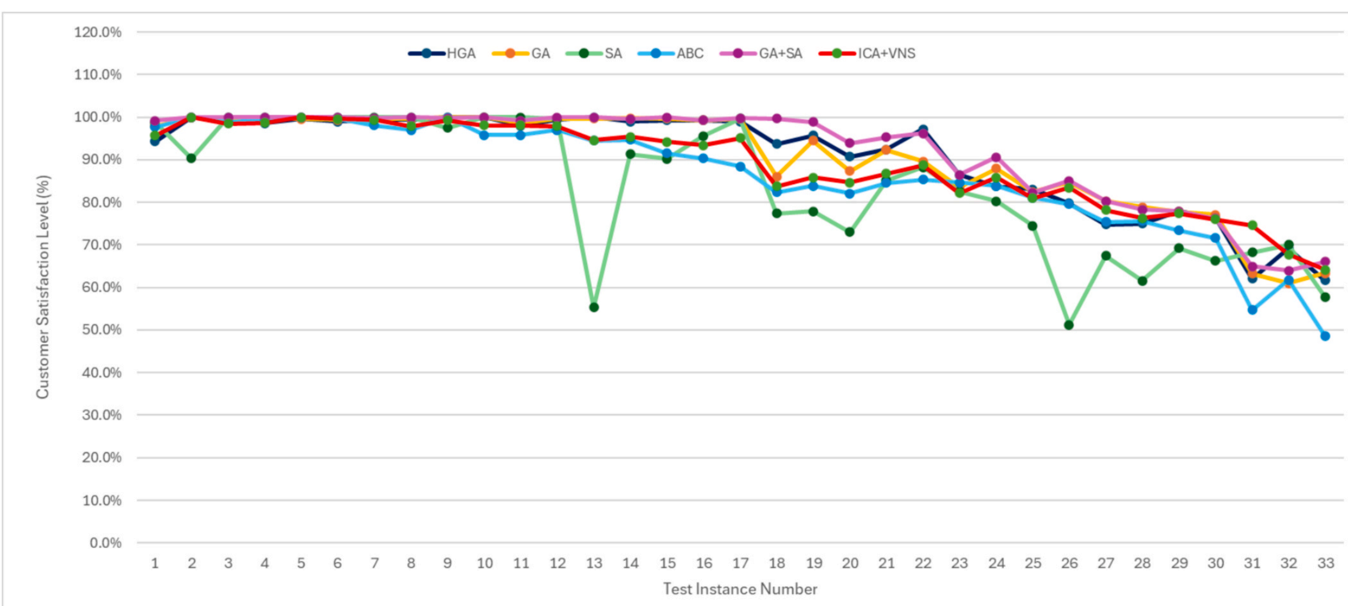


Fig. 8. Customer satisfaction levels across competing algorithms.

changes in customer time window length impact the total supply chain cost.

To explore this, a large-scale scenario with 2,000 customer orders is considered. Results are provided in Table 9. Extending the time window in Scenario 1 has resulted in a total cost reduction of $51,883, which represents a 7.38 improvement in the objective function. In contrast, tightening the time window in Scenario 5 increased the total cost by $101,862 (+14.48), while customer satisfaction dropped to 49.80, reflecting a 12 percent decrease compared to the baseline. Fig. 9 illustrates how the objective function values and customer satisfaction levels vary with time window adjustments.

Overall, expanding the time window enables the timely delivery of

Table 9
Impact analysis of variations in the delivery time slots.

Scenario	Time-window change (E, e, l, L)	Cost ($)	Change from the baseline	Customer satisfaction (%)	Change from the baseline
S1	(0.8, 0.8, 1.2, 1.2)	651 525	−51,883 (−7.38 %)	73,40 %	11,70 %
S2	(0.9, 0.9, 1.1, 1.1)	669 633	−33,774 (−4.80 %)	67,90 %	6,20 %
S3 (Baseline)	(1, 1, 1, 1)	703 408	0 (0.00 %)	61,70 %	0,00 %
S4	(1.1, 1.1, 0.9, 0.9)	765 709	+62,302 (+8.86 %)	55,80 %	−5,90 %
S5	(1.2, 1.2, 0.8, 0.8)	805 269	+101,862 (+14.48 %)	49,80 %	−11,90 %

Fig. 9. Cost and service quality changes with time window variations.

more orders, improving customer satisfaction. However, with tighter time windows, companies may need to acquire more resources and facilities to meet customer demands, leading to increased costs. A more flexible delivery period enhances facility utilization, and reduces penalty costs, ultimately lowering the total supply chain cost.

6. Conclusions and future research

This study contributed a new approach to optimizing food supply chains with mixed last-mile delivery. Considering the interactions between location and time window factors with the routing decisions, ME-OLRPTW with simultaneous home delivery and store pickup points/local depots was proposed to explore e-commerce from the logistics planning perspective. The objective was to minimize supply chain costs while accounting for customer satisfaction by offering on-time and diverse delivery services.

Different test configurations were considered in numerical analysis to evaluate the performance of the proposed algorithm relative to the state-of-the-art. Statistical test confirmed that the developed solution method solves this class of optimization problems more effectively than the state-of-the-art. Sensitivity analysis was also conducted to provide practical insights into planning aspects of the last-mile delivery operations.

This research is limited in that it assumes a static environment with deterministic operational parameters. Future studies should account for such sources of uncertainty to improve the reliability of the optimization outcomes. Simulation-based optimization methods can be tested to address different sources of uncertainties, reduce unrealistic assumptions, and incorporate micro-level production management variables into the optimization model. Additionally, our ME-OLRP formulation can be enhnced using robust optimization approaches and a set-covering model to address ambiguity. The next suggestion comes from the need for the integration of revenue management and menu pricing variables in e-commerce. Prime examples of practical considerations are allowing for splitting orders and conditionally accepting an order while considering service-related performance measures, like the freshness of the products and priority deliveries.

Additional opportunities for future research come from a solution method standpoint. New metaheuristics may improve the solutions provided in this study for the multi-objective optimization of ME-OLRP, considering conflicting profit- and service-oriented goals. From mathematical modeling perspective, the formulation can be extended to account for additional and/or case-specific constraints, and new objective functions, as well as considering multiple planning horizons. Finally, transport-related decision variables for the first and second echelons can be added to the model to account for the possible inbound logistics delays.

CRediT authorship contribution statement

Ali Mokhtari-Moghadam: Data curation, Methodology, Formal analysis, Conceptualization. **Pourya Pourhejazy:** Resources, Writing – original draft, Project administration, Writing – review & editing, Investigation. **Xinan Yang:** Methodology. **Abdella Salhi:** Validation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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