A Two-Echelon Location-Routing Problem for Optimizing Agro-Logistics and Sustainability Enhancement

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Abstract

Contract farming is a modern agribusiness model that has recently been adopted to improve agro-logistics efficiency. The major characteristic of this model is that agricultural products can be supplied directly to the retailers to satisfy their requirements for safe and fresh products. However, as most farms are small-scale and located far from urban areas, the previous method of dispatching vehicles in a single-echelon system from each farm not only consumes a lot of energy and pollutes the environment, but also reduces the income of farmers by paying higher transportation costs as the price of fuel rises. Therefore, to improve the sustainability and feasibility of contract farming transportation, this paper proposes a two-echelon location-routing problem (2E-LRP) to determine the intermediary station locations and routing decisions within the two-echelon system. The objective of the problem is to minimize the total carbon emissions while considering practical environmental constraints including the capacity of facilities and vehicles, agricultural products the impact of the route types and the distance of transportation on the fuel consumption. In addition, an elitism-based genetic algorithm (EGA) is proposed to solve the problem and it is compared with other metaheuristic algorithms. The results show that the proposed EGA can efficiently generate high-quality solutions in test instances of varying scales.

Keywords: Contract farming, Sustainability, Two-echelon location-routing problem, Elitism-based genetic algorithm

1 Introduction

As the global population and economy grows rapidly, the demand for logistics planning in agricultural management has increased significantly. Effective agro-logistics planning not only ensures the quick delivery of fresh products from farms to consumers, meeting market demand, but also reduces transportation and inventory costs, thereby enhancing market competitiveness [1]. Contract farming is one of the modern agricultural business models used to achieve efficient agro-logistics, in which farmers and agribusinesses establish contractual agreements to coordinate production and distribution [2]. Farmers are contracted to produce specified types and quantities of products, which are transported directly to designated locations (e.g., processing plants, supermarkets, or warehouses), while the agribusinesses guide farmers in cultivation practices to improve both the quantity and quality of production and promote environmental sustainability. The advantage of this model is that it ensures a stable, fresh, and safe supply of products [3], and at the same time improves the income of agribusinesses and farmers as well as the sustainable development of society [4].

The echelon logistics system can significantly reduce transportation costs and improve efficiency, especially when facilities are geographically dispersed [5-6]. Unlike traditional direct shipping, the echelon logistics system utilizes intermediary stations as regional distribution hubs within the logistics network. In this system, first-echelon vehicles transport agricultural products from neighboring farms to the intermediary station. From there, second-echelon vehicles deliver the products to customers. This transportation system, involving suppliers, intermediary stations, and customers, is highly cost-effective, complies with working hours and traffic regulations, and has been widely adopted in various industries, such as waste recycling [7], product recycling logistics management [8], and grocery distribution [9].

In recent years, many studies have proposed variants of location-routing problems (LRPs) to determine the optimal routing of two-echelon vehicles within echelon logistics systems [10]. These studies have applied mathematical programming methods or metaheuristic algorithms to solve these problems. For example, Amiri et al. [11] proposed a two-echelon fleet composition mix periodic location-routing problem with time windows (2E-FCMPLRPTW) and employed a Lagrangian decomposition approach to address multi-period location decisions; Pichka et al. [12] formulated the two-echelon open location-routing problem (2E-OLRP) and employed simulated annealing (SA) to plan vehicle routes without returning to intermediary stations; Wang et al. [13] developed the two-echelon multi-period location-routing problem with

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shared transportation resource (2E-MPLRP) and applied particle swarm optimization (PSO) to explore variations in customer demand over time; and Yu et al. [14] proposed the two-echelon multi-objective location-routing problem (2E-MOLRP) and employed a novel genetic algorithm (GA) to address multi-objective problems related to transportation costs and risks. Additionally, Cao et al. [15] proposed the two-echelon biomass resource location-routing problem (2E-BRLRP) and utilized tabu search (TS) and variable neighborhood search (VNS) for biomass energy transportation planning. Moreover, Fallahtafti et al. [16] developed metaheuristic algorithms to assess the risk of cash-in-transit (CIT) in banking operations.

However, most previous studies only focused on minimizing the economic costs, including start-up costs, operating costs, and transportation costs, to maximize economic benefits, while ignoring the negative environmental impacts of energy consumption and carbon emissions during the transportation process, thereby reducing the sustainability of agro-logistics systems. Therefore, this study focuses on the construction and optimization of a two-echelon logistics system for contract farming, aiming to determine the intermediary station locations and the optimal combination of two-echelon vehicle transportation routes under the premise of environmental sustainability.

In this study, a mathematical model of the two-echelon location-routing problem (2E-LRP) is proposed to solve the problem of determining the optimal location of the intermediary station and the optimal transportation routes for the two-echelon vehicles in a contractual agro-logistics network. The objective of the problem is to minimize the total carbon emissions of the two-echelon vehicle routing, considering practical transport constraints such as the impact of distance and road type on vehicle fuel consumption, the production of farms, the capacity of the intermediary station and the processing plant, and the capacity of the vehicles. Since the difficulty of 2E-LRP has been classified as NP-hard, an elitism-based genetic algorithm (EGA) has been proposed to solve this problem efficiently. The feature of the proposed EGA is that a number of solutions with better fitness values in each generation are directly retained in the next generation to avoid them being destroyed by crossover and mutation operators during the improvement process, thus improving the quality and efficiency of the solution. Finally, the proposed EGA is compared with other metaheuristic algorithms such as GA, PSO, and variable neighborhood strategy adaptive search (VaNSAS) in experiments with three different problem scales, and the results show that the proposed EGA can provide better solutions.

The contributions of this paper are organized as follows:

- Different from previous studies focusing on cost or profit, the study focuses on the sustainability of contract agro-logistics networks, and the 2E-LRP is proposed to minimize total carbon emissions from vehicle routing, where the echelon logistics system and location-routin problem are integrated to decide the optimal intermediary station location and the two-echelon vehicle routing.
- The proposed EGA is employed to solve the problem, incorporating an elitism strategy to preserve elite solutions during crossover and mutation operators. Finally, the proposed EGA is shown to outperform other algorithms in terms of computational time and solution quality across different problem scales.

2 Literature Review

This section first reviews the related studies on two-echelon logistics systems, including typical problems such as two-echelon vehicle routing problem (2E-VRP) and 2E-LRP. It then explores metaheuristic algorithms with elitism strategies for efficiently solving these problems.

2.1 Two-echelon Logistics System

A two-echelon logistics system is a cargo distribution system consisting of two echelons of vehicles. The first echelon of vehicles transports the products from the warehouse to the intermediary station, and then the second echelon of vehicles distributes the products to the retailers. In recent years, a complete review of the studies on this system has been carried out. Cuda et al. [17] pointed out that 2E-VRP and 2E-LRP are important issues in two-echelon logistics systems and classified the solution methods for these problems into exact methods, heuristics, and metaheuristics. Sluijk et al. [18] reviewed two-echelon logistics systems, exploring how they address the diversity and challenges of modern logistics demands, including constraints like environmental requirements, vehicle types, and time windows.

This section will review studies on 2E-VRP and 2E-LRP in sequence. First, the 2E-VRP involves determining the optimal routes for vehicles operating at two different echelons. Enthoven et al. [19] designed a 2E-VRP with novel distribution facilities, such as parcel lockers, and developed an adaptive large neighborhood search (ALNS) heuristic algorithm to reduce total operating costs. Li et al. [20] focused on synchronization, where satellites and customers are classified as receiving and delivering, and the problem was solved and compared using mathematical programming and heuristic algorithms based on ALNS. Ramirez-Villamil et al. [21] proposed a 2E-VRP using barges and e-cargo bikes, developing an algorithm based on decomposition strategies to reduce the total time for urban parcel transport. Lehmann and Winkenbach [22] proposed a 2E-VRP mathematical model with time windows and mixed operations of receiving and delivering goods. They used ALNS to solve the problem, demonstrating its superior performance in solution quality and time efficiency, and its widespread application to similar problems over the last decade.

The 2E-LRP is a variant of the 2E-VRP that combines vehicle route planning with facility location decisions. Darvish et al. [23] proposed a flexible 2E-LRP considering delivery time windows and daily distribution center location choices. They solved this using branch-and-bound algorithms to minimize total costs, including distribution center rental costs, transportation costs, and penalty costs for unmet customer due dates, achieving an average cost saving of 30%. Pitakaso et al. [24] introduced a 2E-LRP for the rubber industry and solved it using the VaNSAS algorithm to reduce total transportation fuel consumption by optimizing facility siting and transportation routes. Du et al. [25] focused on a joint delivery-based 2E-LRP and proposed a hybrid immune algorithm and improved non-dominated sorting genetic algorithm II (iNSGA-II) to solve this complex problem. Tian and Hu [26] developed a mathematical model for 2E-LRP to minimize total costs, including transportation costs of two-echelon routes, facility rental costs, and penalties for missed deadlines, demonstrating the potential of the branch pricing approach in solving this complex logistics problem.

2.2 Elitism-based Genetical Algorithm

Metaheuristic algorithms have been widely employed in the optimization of complex problems in many domains over the past decade, as traditional deterministic methods find it difficult to effectively deal with their complexity and highly structured nature. To further improve the solution quality of these algorithms, many studies have combined elitism strategies with metaheuristic algorithms to achieve faster search and higher accuracy, making hybrid methods important in solving such problems. Raut and Mishra [27] proposed a modified Elitist-Jaya algorithm to optimize the power distribution system, incorporating several improved strategies, including linear decreasing inertia weight, neighborhood search, and elitism strategy. Abuhamdah [28] developed an adaptive elitist-ant system based on ant colony optimization (ACO) to address the clustering problem of medical data, aiming to enhance data processing efficiency in medical diagnosis and research. Zhang et al. [29] integrated an EGA with two elitism-based crossover mechanisms and TS to solve the quadratic assignment problem (QAP), demonstrating superior performance in most of the 131 instances compared to other popular metaheuristic algorithms in the literature. Natesha et al. [30] developed a multi-objective optimization approach based on the EGA for solving task scheduling problems in a fog computing environment. Chen et al. [31] developed an EGA with a neighborhood search mechanism for a flexible job shop scheduling problem (FJSP), showing favorable performance compared to four other algorithms. Zhang et al. [32] proposed a novel metaheuristic-inspired algorithm based on a self-adaptive response strategy and the elitism strategy, capable of finding high-quality solutions in multi-objective optimization problems while maintaining solution diversity and convergence performance. Moazen et al. [33] introduced a PSO with an elitism strategy, utilizing the selection of the best-performing particles (elites) in the swarm to enhance solution quality. The results indicated that the proposed algorithm is an efficient and reliable method for various multi-objective optimization problems.

3 Problem Description and Model Formulation

This study proposes the 2E-LRP for agro-logistics, which transports agricultural products from farmland to destination facilities. First, the objectives and constraints of the problem are described, followed by the mathematical model.

3.1 Problem Description

There is a two-echelon logistics system network, in which there is a depot and a collection of farmland N, and the agriculture produce is Q_i and all of them are candidates for intermediary stations. In the network, there are two echelon vehicles with different capacities to transport agricultural products. Firstly, a small vehicle (i.e., the second echelon vehicle) from the intermediary station collects the agricultural products from the designated farmland and returns; then a large vehicle (i.e., the first echelon vehicle) from the factory collects the agricultural products from all the intermediary stations. Each farm and intermediary station can only be visited once by a vehicle, and there are no routes between intermediary stations. All facilities, including factories, intermediary stations and two-echelon vehicles, are subject to capacity constraints. In addition, the distance travelled by all routes and the fuel consumption of the vehicles on different types of routes are known.

The selection of the intermediary station locations and the routing of the two-echelon vehicles will directly affect the carbon emissions from the vehicles. Therefore, the objective of the problem is to minimize the total carbon emissions from vehicles, considering a number of agro-logistics operating conditions including transport distance, fuel consumption of vehicles by route type, farmland output, and capacity constraints (e.g., capacity of the vehicles, capacity of the intermediary station, and capacity of the processing plant).

3.2 Model Formulation

The mathematical model of 2E-LRP is proposed, and the corresponding notation is presented in Table 1.

Table 1. Mathematical notation used in the model

Parameters / Sets	
N	The set of all farms indexed by i and j.
N^+	The set consisting of all the farms and a plant.
K	The set of all vehicles in both of two echelons.
Data	
D_{ij}	The distance from node i to node j (km), $D_{ij} > 0$.
F_{ij}	The fuel consumpition from node i to node j (liter), $F_{ij} > 0$.
C^1	The carbon emission factor of vehicles in the first echelon, C^2= 2.68 (kg-CO_2 /liter).
C^2	The carbon emission factor of vehicles in the second echelon, C^2 = 2.31 (kg-CO_2 /liter).
S	The number of collection stations selected from the farms in set N.

U	The minimum number of farms served by each collection station, $U = \|N\| / S-1$.
Q_i	The agricultural yield of farm i.
M	Maximum value.
V^1	The capacity of vehicles in the first echelon, $V^1 > 0$.
V^2	The capacity of vehicles in the second echelon, $V^2 > 0$.
Desicion variables	
x_{ijk}	1, if the first-echelon vehicle k is scheduled to serve collection station j after station i; 0, otherwise.
y_{ijs}	1, if the second-echelon vehicle departing from collection station s is scheduled to serve farm j after serving farm i; 0, otherwise.
b_{isk}	1, if the farm is assigned to the collection station served by vehicle k; 0, otherwise s.
q_{sk}	The loads on the first-ehcelon vehicle k that departs from the plant after servicing station s.
p_{is}	The load on the second-echelon vehicle that departs from collection station s after servicing farm i.

Mathematical model:

$$Min\ f = f^1 + f^2 \tag{1}$$

subject to:

$$f^1 = C^1 \cdot \sum_{k \in K} \sum_{i \in N^+} \sum_{j \in N^+} \left(D_{ij} \cdot F_{ij} \cdot x_{ijk} \right) \tag{2}$$

$$f^2 = C^2 \cdot \sum_{s \in N} \sum_{i \in N} \sum_{j \in N} \left(D_{ij} \cdot F_{ij} \cdot y_{ijs} \right) \tag{3}$$

$$\sum_{k \in K} x_{iik} = 0,\ \forall i \in N \tag{4}$$

$$\sum_{i \in N^+} x_{ijk} = \sum_{i \in N^+} x_{jik},\ \forall j \in N,\ \forall k \in K \tag{5}$$

$$\sum_{j \in N^+} x_{ijk} = b_{iik},\ \forall i \in N,\ k \in K \tag{6}$$

$$\sum_{j \in N} x_{0jk} = 1,\ k \in K \tag{7}$$

$$\sum_{k \in K} y_{iis} = 0,\ \forall i \in N \tag{8}$$

$$\sum_{i \in N} y_{ijs} = \sum_{k \in K} b_{jsk},\ \forall j,\ s \in N \tag{9}$$

$$\sum_{i \in N} y_{jis} = \sum_{k \in K} b_{jsk},\ \forall j,\ s \in N \tag{10}$$

$$\sum_{k \in K} b_{iik} \leq 1,\ \forall i \in N \tag{11}$$

$$\sum_{k \in K} \sum_{s \in N} b_{ssk} = S \tag{12}$$

$$\sum_{k \in K} \sum_{s \in N} b_{isk} = 1,\ \forall i \in N \tag{13}$$

$$\sum_{k \in K} \sum_{s \in N, s \neq i} b_{isk} = 1 - b_{iik},\ \forall i \in N \tag{14}$$

$$b_{isk} \leq b_{ssk},\ \forall i,\ s \in N,\ \forall k \in K \tag{15}$$

$$\sum_{i \in N} b_{isk} \geq U \cdot b_{ssk},\ \forall s \in N, k \in K \tag{16}$$

$$q_{ik} + \sum_{s \in N} Q_s \cdot b_{sjk} - M \cdot \left(1 - x_{ijk}\right) \leq q_{jk},\ \forall i \in N^+,\ j \in N,\ k \in K \tag{17}$$

$$p_{is} + Q_j - M \cdot \left(1 - y_{ijs}\right) \leq p_{js},\ \forall i \in N,\ j \in N,\ j \neq s,\ s \in I \tag{18}$$

$$\sum_{i \in I} \sum_{j \in J} Q_i \cdot b_{ijk} \leq V^1,\ \forall k \in K \tag{19}$$

$$\sum_{i \in I} Q_i \cdot b_{ijk} \leq V^2,\ \forall j \in N,\ k \in K \tag{20}$$

$$x_{ijk} \in \{0,1\},\ \forall i,\ j \in N^+,\ k \in K \tag{21}$$

$$y_{ijs} \in \{0,1\},\ \forall i,\ j,\ s \in N \tag{22}$$

$$b_{isk} \in \{0,1\},\ \forall i,\ s \in N,\ k \in K \tag{23}$$

$$q_{ik} \geq 0,\ \forall i \in N^+,\ k \in K \tag{24}$$

$$p_{is} \geq 0,\ \forall i, s \in N \tag{25}$$

The objective function (1) is to minimize the total carbon emissions of the echelon 1 and echelon 2 vehicle routes. The carbon emissions of the first and second echelon are determined by Constraints (2) and (3) respectively. Constraints (4)-(7) are the limitation of the first echelon vehicle route, where the vehicle travels from the factory to the intermediary station. Constraint (4) means that it is not allowed for the intermediary station to have its own route. Constraint (5) is to ensure flow conservation of the first-echelon vehicles. Constraints (6) and (7) ensure that each intermediary station is served by vehicles travelling from the factory. Constraints (8)-(10) describe the second-echelon vehicle routes from intermediary stations to farms. Constraint (8) indicates that it is not permissible for the farmland to have its own route. Constraints (9) and (10) ensure that the second echelon vehicle traffic is conserved. Constraints (11)-(16) are restrictions on the siting of intermediate stations. Constraint (11) ensures that each intermediary station is visited by first echelon vehicles at least once. Constraint (12) limits the total number of intermediary stations. Constraints (13) and (14) indicate that each farm is to be assigned to an intermediary station, except for those farms selected as intermediary stations. Constraints (15) and (16) ensure that farmland is assigned to all selected intermediary stations in a balanced manner. Constraints

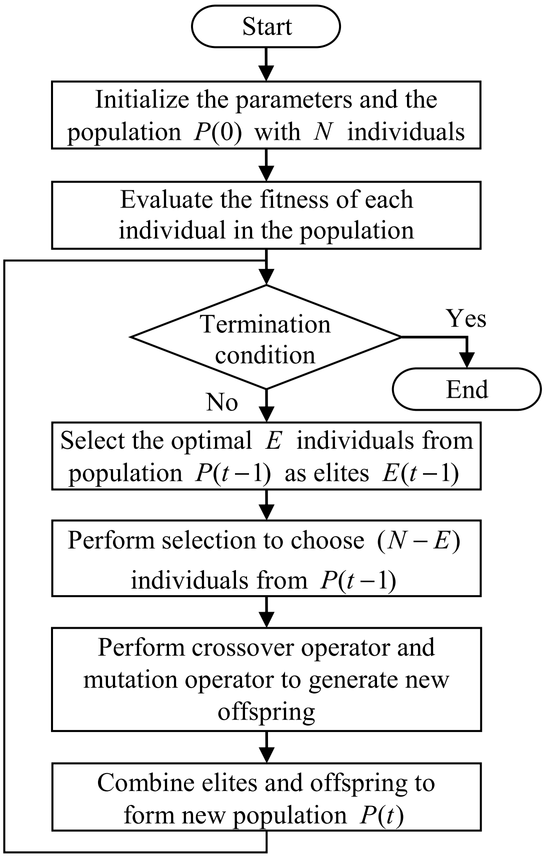
(15)-(18) are capacity limits for the two-echelon vehicles. Constraints (19) and (20) limit the capacity of all vehicles to be met. Constraints (21)-(25) define all decision variables in the model.

4 The Proposed Approach

The 2E-LRP is in fact an NP-hard problem [34], and as the size of the problem increases, it is difficult to apply it in practice because of the difficulty in obtaining the optimal solution in effective time using the traditional exact methods. Therefore, this study introduces an EGA to solve the problem of this study in order to improve the efficiency of agricultural product delivery. The proposed EGA combines GA and an elitism strategy, which is a metaheuristic algorithm based on the principles of natural selection and genetics, and its advantage is that the operation process can be flexibly adjusted according to the specific problem to adapt to different application requirements [35]. On the other hand, the elitism strategy improves the convergence and stability of metaheuristic algorithms on complex optimization problems by retaining the optimal solutions [36].

The procedure of performing EGA is presented in Table 2, which consists of four main parts: solution representation, fitness value calculation, solution improvement (including the execution of elitist selection, crossover and mutation), and iteration termination conditions.

Table 2. The flowchart of EGA



4.1 Solution Representation

This part describes the encoding and decoding of the solution. Firstly, the method proposed in [24] is used to encode the individual chromosome of the EGA, whose structure can be expressed as $X = [C, R]$, including the set of intermediary station candidates (or the set of farmlands) $C = \{x^c_i, x^c_i = 1, 2, ..., N\}$ and the set of vehicle routes $R = \{x^r_i, x^r_i = 0, 1, 2, ..., N\}$. The LH $(= 2 \cdot N + S - 1)$ of the chromosome can be computed, where the N and the S denote the number of farmland and the number of intermediary stations, respectively.

An example is then given to illustrate the above chromosome decoding. For example, let $N = 5$, $S = 2$, a chromosome is generated randomly $X = \{(2, 4, 3, 5, 1), (4, 5, 0, 3, 1, 2)\}$ with length 11 $(= 2 \cdot 5 + 2 - 1)$, which is decoded according to the following three steps:

- Step 1: Confirm the location of the intermediary station. From the candidate set of intermediary stations, $C = \{2, 4, 3, 5, 1\}$ selects the top S elements as intermediary stations (i.e. farmland 2 and 4 are intermediary stations).
- Step 2: Determine the second echelon of vehicle routes (i.e., the vehicle routes of the intermediary stations). Firstly, cut the 0's of the set $R = \{4, 5, 0, 3, 1, 2\}$ of vehicle routes and assign them to the intermediary stations 2 and 4 respectively in order to obtain two vehicle routes. The first vehicle route is 2-5-2 (i.e., from the intermediary station 2 to the farmland 5, and then back to the intermediary station 2); and the second vehicle route is 4-3-1-4 (i.e., from the intermediary station 4 to the farmland 3 and 1, and then back to the intermediary station 4).
- Step 3: Finally, the first echelon of vehicle routes (i.e., the factory's vehicle routes) is also depot-2-4-depot.

4.2 Fitness Evaluation

The quality of each individual in EGA can be determined based on the fitness value. The fitness value of each individual can be calculated by Eq. (26), which is a combination of Constraints (2), (3), (19) and (20), where δ_1 and δ_2 are the penalty costs for the first and second echelons, respectively.

$$\begin{aligned} f = {} & C^1 \cdot \sum_{k \in K} \sum_{i \in N^+} \sum_{j \in N^+} \left(D_{ij} \cdot F_{ij} \cdot x_{ijk} \right) \\ & + C^2 \cdot \sum_{s \in N} \sum_{i \in N} \sum_{j \in N} \left(D_{ij} \cdot F_{ij} \cdot y_{ijs} \right) \\ & - \delta_1 \cdot \max_{\forall k \in K} \left(\sum_{i \in I} \sum_{j \in J} Q_i \cdot b_{ijk} - V^1, \ 0 \right) \\ & - \delta_2 \cdot \max_{\forall j \in N,\, k \in K} \left(\sum_{i \in I} Q_i \cdot b_{ijk} \le V^2, \ 0 \right) \end{aligned} \tag{26}$$

Since the objective of this study is to minimize the total carbon emissions of the two echelons of vehicles, the smaller the fitness value of an individual means the better the solution to the problem obtained.

4.3 Solution Improvement

This section explains the solution improvement process of the EGA, including elitist selection, crossover, and mutation operators.

Elitist selection operator

The purpose of the elitist selection operator is to select a few individuals with better fitness values from the current population and retain them to the next generation, so as to minimize their damage in crossover and mutation operators and to improve the solution quality. In this operator, the fitness values of all individuals in the current generation are sorted from low to high, and the elite individuals with smaller fitness values are retained to the next generation. Some literature suggests that the number of elites should be set low to prevent rapid convergence into local optimal solutions [30].

Corssover operator

A crossover operator aims to recombine the chromosomes of two or more individuals in the current generation population to produce new individuals, thereby increasing the probability of finding the best solution. In this study, a single-point crossover is used to generate new chromosomes. This process involves selecting a pair of individuals from the population, randomly choosing a chromosome location as the crossover point, and then exchanging the blocks after the crossover point to form two new individuals.

Mutation operator

A mutation operator is the process of altering some genes in a new individual after crossover to increase the diversity of the population and avoid falling into local optima. In this study, the mutation process involves randomly exchanging genes within two blocks of the chromosome, namely the intermediary station candidate block and the vehicle route block.

4.4 Termination Condition

In this study, the improvement process of the previous solution will continue until the maximum number of iterations of the algorithm is reached. While increasing the number of iterations enhances the likelihood of finding a better solution, it also raises computation time. Therefore, the convergence of the algorithm will be analyzed experimentally to determine the optimal setting for the maximum number of iterations.

5 Experimental Analysis

In this section, this study performed numerical experiments to evaluate the performance of the EGA solution for the proposed 2E-LRP, and the details of the three scales of numerical experiments are presented in Table 3. The values of vehicle fuel consumption for each road type can be found in the literature [24]. Before experimenting, the parameters of EGA are analyzed and set up in this study, and then EGA, GA, PSO and VaNSAS [24] are run to analyze the results of their comparisons in all scales. The computational environment for this study includes an Intel Core i7-9700 CPU at 3.00 GHz, 16 GB of RAM, and a 64-bit Windows 10 platform, with Python as the development tool.

Table 3. The information of the numerical experiments

Parameters	Small	Medium	Large
Number of fall land	20	40	80
Number of intermediary stations	6	14	19
Farmland output (kg)	148,089	291,702	526,630
First echelon capacity (kg)	30,000	30,000	30,000
Second echelon capacity (kg)	15,000	15,000	15,000
Intermediary station capacity (kg)	30,000	30,000	30,000
Factory capacity (kg)	300,000	300,000	600,000

5.1 Parameter Analysis

A series of preliminary experiments was first conducted using a small-scale test case to achieve better performance of the proposed EGA. The parameter settings reported in [30] were also adopted as the reference basis for parameter design and adjustment. Several important parameters in the EGA were carefully examined during the experiments, including population size (N), crossover rate (P_c), mutation rate (P_m), elitism rate (P_e), and iteration number (NI). The results corresponding to these parameter settings are presented in Table 4.

Table 4. Parameter settings of the EGA

Parameters	Testing values	Optimal value
N	60, 80, 100, 120, 140	120
P_c	0.5, 0.7, 0.9, 0.95,0.99	0.95
P_m	0.2, 0.25, 0.3, 0.35, 0.4	0.3
P_e	0.04, 0.06, 0.08, 0.1, 0.12	0.08
NI	0 ~ 20,000	10,000

5.1.1 Population Size (N)

This part analyzes the optimal population size in EGA. Based on the population size of 100 in [30], five parameter values (60, 80, 100, 120, and 140) are designed and analyzed. Figure 1(a) shows the analysis results of the population size, which indicates that the fitness value is minimized when the population size is set to 120 in 10,000 iterations of the algorithm. In addition, the fitness value decreases gradually as the population size increases, but too many chromosomes will deteriorate the quality of the solution. Therefore, the number of chromosomes of EGA is set to 120.

5.1.2 Crossover rate (P_c), Mutation rate (P_m), and Elitism Rate (P_e)

This part optimizes the crossover rate, mutation rate, and elitism rate in EGA. Referring to the suggestion in [30], the crossover rate is set to 0.5, the mutation rate to 0.3 and the elitism rate to 0.08, and several experimental parameter values are designed. Firstly, in the crossover rate experiment, five values are tested: 0.5, 0.7, 0.9, 0.95 and 0.99. From Figure 1(b), it can be seen that the crossover operator enhances the fitness value of the solution, and the best effect is achieved when the crossover rate is set to 0.95. However, a crossover rate that is too high (i.e., more than 0.95) reduces the number of chromosomes generated by the randomized approach, decreasing the diversity of solutions and making it more difficult to obtain better solutions. Next, in the mutation rate experiment, five values of mutation rate are tested: 0.2, 0.25, 0.3, 0.35, and 0.4. From Figure 1(c), it can be found that the best result is achieved when the mutation rate is set at 0.3.

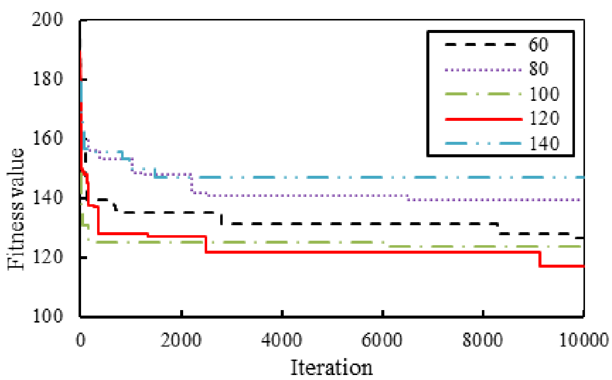
Finally, the elitism rate is analyzed. According to the suggestion of [30], the elitism rate should not be set high to avoid the algorithm degrading due to rapid convergence. Therefore, five values of the elitism rate are tested: 0.04, 0.06, 0.08, 0.1 and 0.12, and a small number of elites from the parent population are directly retained to the next generation. Figure 1(d) shows the experimental results of elitism rate, and the best effect is achieved when the elitism rate is set to 0.08. Hance, the crossover, mutation, and elitism rates are set to 0.5, 0.3, and 0.08, respectively.

5.1.3 Iteration (*NI*) Analysis

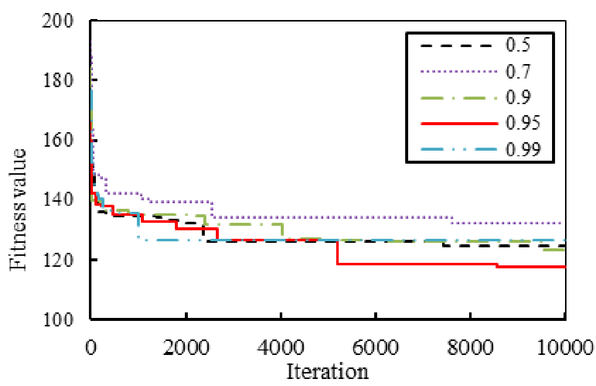
For the purpose of determining the optimal number of iterations for the EGA, four methods (i.e., EGA, GA, PSO, and VaNSAS) are executed in a small-scale case to observe the number of suitable iterations. From Figure 1(e), it can be seen that when the number of iterations is between 5,000 and 20,000, the changes in fitness value become negligible. Therefore, the number of iterations is set to 10,000.

5.2 Experimental Results

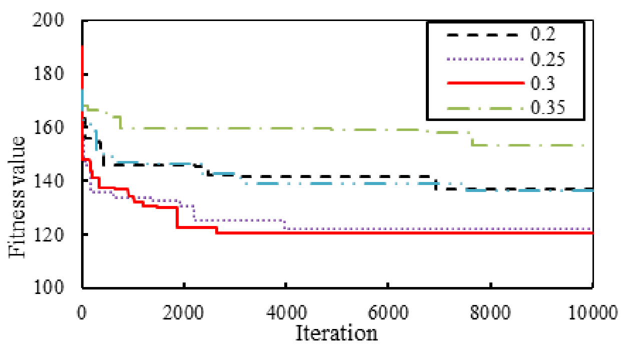
This part compares EGA with GA, PSO, and the local search-based VaNSAS method.To ensure the fairness of the experiment, the settings of the population size (i.e. N=100) and the number of iterations (i.e. NI=10,000) are the same for each algorithm in the experiment and their respective parameters are optimized. Table 5 shows the comparison results of all the algorithms, in which the comparison items include the best fitness value, the average fitness value, the worst fitness value, the standard deviation, and the average computational time, and all the algorithms are executed 20 times in each test case. From Table 5, it can be found that EGA outperforms the other methods in all three test cases, and the performance of EGA becomes more significant as the test cases become larger. The performance of the methods in the small-scale test cases ranks as EGA > GA > VaNSAS > PSO, while in the medium- and large-scale test cases, the ranking is EGA > GA > PSO > VaNSAS.



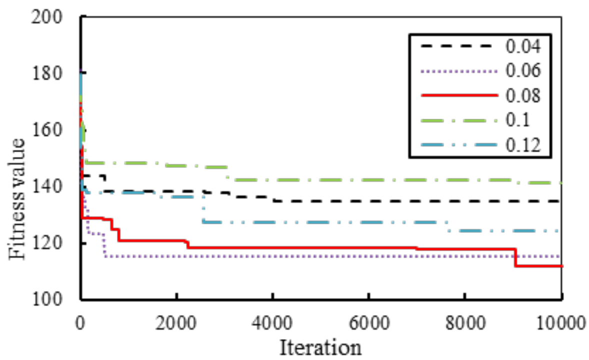
(a) Population size



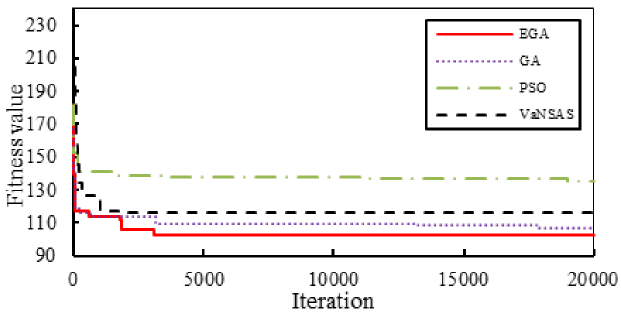
(b) Crossover rate



(c) Mutation rate



(d) Elitism rate



(e) Iterations

Figure 1. Analysis of EGA parameters setting

Table 5. Comparison results of the four methods for the three sizes of testing examples

Problem scales	Methods	Best fitness value	Average fitness value	Worst fitness value	Standard deviation	Average time (min)
Small	EGA	102.30	114.25	135.99	13.13	20.11
	GA	106.70	122.81	137.97	12.48	17.82
	PSO	135.52	144.54	155.34	7.09	16.14
	VaNSAS	116.53	126.81	239.54	55.72	717.00
Medium	EGA	284.68	325.65	355.33	28.97	48.99
	GA	297.17	339.57	374.70	31.70	36.91
	PSO	313.79	336.95	376.47	25.88	39.42
	VaNSAS	350.00	353.23	475.19	58.27	>1440
Large	EGA	573.69	606.18	634.32	24.77	84.03
	GA	606.05	675.04	723.94	48.36	73.29
	PSO	640.21	673.78	706.54	29.18	64.96
	VaNSAS	666.75	666.83	759.82	43.85	>1440

6 Conclusion

Contract farming ensures stable agro-logistics through agreements between agribusiness and farmers. However, as increasing emphasis on sustainable agriculture, contract farming faces a significant challenge in quickly delivering fresh produce from farms to markets while reducing energy consumption and transportation costs. To address this challenge, this study proposes a two-echelon location-routing problem aimed at determining the optimal location of transfer stations and vehicle routes to minimize the total carbon emissions of vehicle routes. The problem takes into account various practical environmental constraints including transport distance, road type, farmland output, and the capacities of intermediary stations and processing plants, as well as vehicle capacity. To effectively solve this complex problem, this study introduces an elitism-based genetic algorithm, which includes an elite mechanism that retains several high-fitness solutions from the current parent population directly into the next generation, reducing their destruction by traditional crossover and mutation operators. The numerical experiment results show that EGA outperforms typical metaheuristic algorithms such as GA, PSO, and VaNSAS in terms of solution quality, especially as the scale of the test cases increases. This approach can help managers of agricultural organizations or agribusinesses quickly and flexibly generate feasible solutions according to actual operational needs, thereby improving decision-making efficiency and resource allocation performance.

Future research will consider multi-objective problems such as transportation risk and penalty costs for unmet customer demand to enhance the study's practical usefulness. Additionally, with the rise of smart agriculture, future studies will explore the application of electric vehicle transportation and utilize the Internet of Things and artificial intelligence technologies to collect and analyze information during the transportation process.

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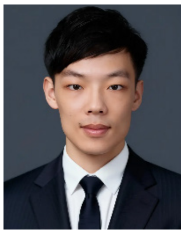

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