Research on Low-Carbon Fresh Produce Logistics Route Optimization Based on an Improved Particle Swarm Algorithm

Yanbing Gai, Liying Li*

School of Business and Management, Liaoning Technical University, Huludao, Liaoning, 125100, China

*506663608@qq.com

Abstract. In the context of striving to enhance the efficiency of fresh produce logistics distribution and achieving energy saving and emission reduction goals, this paper delves into the optimization of fresh produce logistics routes based on electric vehicles. Considering the unique requirements of fresh produce delivery, the paper comprehensively examines factors such as transportation costs, carbon emissions, refrigeration effects, goods damage, and time window constraints to construct an optimization model aimed at minimizing total costs. Compared to existing literature, this study particularly emphasizes a thorough consideration of the costs associated with goods damage, aiming to ensure high precision in the model through more detailed and comprehensive analysis. To solve the model, an improved particle swarm algorithm is introduced. The effectiveness of the optimization model and algorithm is validated using the Solomon dataset. Experimental results indicate that the model performs well in reducing total costs and enhancing delivery efficiency. Specifically, it achieved an average reduction of 14.52% in total costs, a 41.15% decrease in carbon emissions, and a significant reduction in time window violations, averaging a 30.83% decrease.

Keywords: Fresh Produce Logistics; Low-Carbon; Electric Vehicle Delivery; Route Optimization; Improved Particle Swarm Algorithm

1 INTRODUCTION

The commitment to reach a carbon peak by 2030 and achieve carbon neutrality by 2060 has intensified carbon emission constraints on high-carbon industries, necessitating significant technological upgrades and innovations for a transition to a low-carbon economy. This is particularly relevant in the fresh produce transportation sector, where substantial amounts of carbon dioxide are emitted during transportation and refrigeration processes. Consequently, the adoption of electric vehicles for the delivery of fresh produce has emerged as a new and sustainable distribution model.

Numerous scholars have studied the distribution of fresh produce logistics. Shen Li[1] conducted a detailed analysis of goods damage and carbon emissions, establish

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ing an optimization model aimed at minimizing total costs, and solved it using a genetic algorithm. Wu[2] considered the cost of carbon taxes, utilizing an improved A* algorithm and ant colony optimization to construct a delivery model with an objective function aimed at minimizing total costs while maximizing satisfaction. Wen Tingxin[3], from a low-carbon perspective, used a knowledge-based ant colony algorithm to optimize and construct a route optimization model for electric vehicles with soft time windows and multi-temperature co-distribution. Wen Tingxin[4] and others developed an optimization model for multi temperature joint allocation paths in electric vehicles in a time-varying network with a soft time window, taking into account carbon emissions. Liu[5] and others developed an integer programming model aimed at minimizing total costs, using a genetic algorithm to extensively study the two-level route optimization problem from "production site to multiple distribution centers to multiple customers.

In recent years, some scholars have also focused on the optimization of electric vehicle routes. Mavrovouniotis[6] and colleagues incorporated electric vehicle charging strategies into their considerations and planned EV routes using an improved ant colony algorithm. Song Liying[7] and others considered carbon emissions and customer time windows, and established a route optimization model for mixed fleets of fuel vehicles and electric vehicles using an improved ant colony algorithm. Alizadeh[8] took into account electric vehicle charging locations, charging amounts, and dynamic electricity pricing based on location to optimize EV routing and charging path planning. Jiu Yanni[9] considered that different fresh products have different requirements for freshness, so they proposed the concept of freshness coefficient for fresh products, and thus constructed a freshness difference function for fresh agricultural products. They designed a hybrid particle swarm algorithm to solve the problem.

In summary, scholars both domestically and internationally have extensively studied the optimization of fresh produce delivery routes using electric vehicles. However, there has been a lack of detailed consideration of carbon emissions and goods damage associated with electric vehicles. Building on previous research, this paper categorizes goods damage costs into three types: damage due to loading and unloading or collisions, damage from the respiration of fresh produce, and damage due to temperature changes when refrigerated truck doors are opened during unloading. It also considers various costs associated with vehicle emissions, transportation, refrigeration, and time window violations. An optimization model aimed at minimizing total costs is constructed and solved using an improved particle swarm algorithm. The effectiveness of the model and algorithm is validated through simulation experiments.

2 MATHEMATICAL MODEL

2.1 Problem Description and Hypothesis

To ensure the completeness of the model construction in this paper, the following assumptions are made regarding the problem:

(1) Electric refrigerated trucks depart from and return to the distribution center.

(2) Electric refrigerated trucks start their journey from the distribution center at full battery capacity. When the vehicle's battery level is low, it needs to recharge quickly at customer points, incurring a certain cost.

(3) The study focuses on a single distribution center serving multiple customer points.

(4) Fresh produce distribution is unidirectional, with each customer being served only once.

(5) Distances between nodes are known, and the vehicle's speed is fixed.

These assumptions help simplify the complexity of the problem and facilitate the establishment and solution of the model. However, it is necessary to explicitly state in the discussion and conclusion sections how these assumptions affect the research results.

2.2 Symbol Description

The symbols and meanings of the problems in this paper are shown in Table 1.

Table 1. Problem symbol and meaning description

Symbol	Meaning description
0	Distribution center, starting from 0 and ending at 0 '
N	Customer point collection, N={1,2···N}
K	Electric refrigerated vehicle collection,K={1,2···K}
d_{ij}	The distance from node i to node j
u	Time window penalty coefficient
t_i	The time when the vehicle arrived at point i
x_{ijk}	Variable 0-1, vehicle traveling from i to j is 1; Otherwise zero
y_{ik}	Variable 0-1, vehicle at point i for service is 1； Otherwise zero

2.3 Objective Function

The objective of this study is to establish an optimization model for the delivery routes of electric refrigerated vehicle fleets distributing fresh goods, aiming to minimize the total cost. The total cost is composed of fixed costs (C1), transportation costs (C2), penalty costs for time window violations (C3), refrigeration costs (C4), product damage costs (C5), and carbon emission costs (C6). A detailed analysis of these costs is provided below:

(1) Fixed Costs

Fixed costs are directly proportional to the quantity of electric refrigerated vehicles. As the number of vehicles increases, the fixed costs also rise accordingly.

$$C_1 = m_1 \sum_{k \in K} \sum_{j \in N} x_{0jk} \tag{1}$$

In the equation, m1represents the fixed cost per unit of electric refrigerated vehicle.

(2) Transportation Costs

Transportation costs are determined by the cost of electricity consumed during the delivery process and are directly proportional to the driving distance of the electric refrigerated vehicles.

$$C_2 = \mathrm{m}_2 \sum_{\mathrm{k}\in K} \sum_{i\in N} \sum_{j\in N} d_{ij} x_{ijk} \tag{2}$$

In the formula, m2 represents the unit transportation cost of an electric refrigerated vehicle.

(3) Time Window Penalty Costs

Time window penalty costs are incurred when a delivery vehicle arrives at customer i at a time ti that is outside the acceptable service time window [ei, li].

$$C_3 = \begin{cases} u_1(e_i - t_i) & 0 < t_i \le e_i \\ 0 & e_i < t_i \le l_\mathrm{i} \\ u_2(t_i - l_i) & t_i > l_i \end{cases} \tag{3}$$

(4) Refrigeration Costs

Electric refrigerated vehicles use electricity as their power source, with batteries supplying power to operate the refrigeration units. These units rely on the cyclical changes of refrigerant through the compressor, condenser, expansion valve, and evaporator, along with the precise regulation by an intelligent control system, to maintain a low-temperature environment within the vehicle.

$$C_4 = \mathrm{m}_3 \sum_{k\in K} \sum_{i\in N} \sum_{j\in N} t_{ij} x_{ijk} + m_4 \sum_{k\in K} \sum_{j\in N} s_{ik} y_{ik} \tag{4}$$

In the formula, the first and second terms represent the refrigeration costs incurred during vehicle transportation and at the point of unloading at location i , respectively. Here, m3 denotes the unit refrigeration cost per unit of time during transportation, m4 represents the unit refrigeration cost per unit of time during unloading services, and sik indicates the service time of vehicle k at location i.

(5) Product Damage Costs

Fresh products are notably perishable. Based on an analysis of actual damage scenarios, the damage to fresh products can be categorized into three parts:

5.1 Damage during loading and unloading, and from collisions. The bumps and jolts that occur during the handling and transportation of products can cause actual damage to fresh goods.

$$C_{51} = \sum_{k\in K} \sum_{i\in N} (y_{ik} p \vartheta q_i) \tag{5}$$

In the equation, p represents the unit value of the fresh products, ϑ denotes the damage rate of the fresh products, and qi indicates the demand quantity of fresh products by customer i.

5.2 Damage caused by respiration is represented by a continuous lifecycle function that describes the exponential decay of fresh products over time. This lifecycle function aptly reflects the spoilage characteristics of fresh products. The remaining quality of the fresh products after time t (i.e., the decay function of the fresh products) is given by:

$$Q(t) = e^{-\partial_1 t} \tag{6}$$

To better depict the function, the Arrhenius equation is introduced to express the relationship between the reaction rate g and temperature T, which improves the model for Q(t) :

$$g = Ue^{-E/LT} \tag{7}$$

$$Q(t) = ge^{-\partial_1 t} \tag{8}$$

In the equation, E represents the activation energy of the reaction, and U is the frequency factor; both parameters are empirical constants derived from research. L denotes the gas constant, while ∂_1 and ∂_2 represent the spoilage rates of fresh products, which are dependent on temperature. The cost of product damage caused by respiration during transportation, after the refrigerated vehicle departs from the distribution center, is:

$$C_{22} = \sum_{k \in K} \sum_{i \in N} (y_{ik} p q_i (e^{-\partial_1 t_0} - ge^{-\partial_1 (t_{ki} + t_0)})) \tag{9}$$

In the equation, t0 represents the total time from when the fresh products are harvested to when they are transported and stored at the distribution center. tki denotes the time it takes for vehicle k to travel from the distribution center to customer location i.

5.3 Damage during unloading due to temperature changes caused by opening the doors of the refrigerated vehicle. After the doors of the refrigerated vehicle are opened, the function describing the change in the interior temperature (Tin) is derived from data fitted according to measurements by Lv Ning [10]:

$$T_{in} = \begin{cases} 2.65\ln t + 14, & 0 < t < t_1 \\ T_2, & t_1 \le t \le t_2 \\ -4t + 4s_{ik} + 4, & t_2 < t \le s_{ik} \end{cases} \tag{10}$$

After the doors are opened, the interior temperature of the vehicle Tin suddenly rises and then stabilizes; when the doors are closed, Tin gradually decreases. The trend of Tin over time t is shown in Figure 1. In Figure 1: T1 is the interior temperature during transportation; T2 and t1 represent the steady temperature reached inside the compartment after the doors are opened and the time required to reach this steady temperature, respectively; t2 is the time when the doors are closed. The spoilage rate of fresh products ∂_2 also varies with temperature, described by a linear function using the formula proposed by Mukhopadhyay:

$$\partial_2 = aT_{in} \tag{11}$$

In the equation, a is a coefficient, which is a constant value. The cost of product damage incurred due to opening the doors for unloading upon arrival at customer i is:

$$C_{53} = \sum_{k\in K}\sum_{i\in N}(y_{ik}pq_i(e^{-\partial_1 t_0} - ge^{-\partial_2(t_i+t_0)})) \tag{12}$$

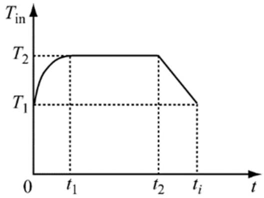

Fig. 1. Temperature changes inside the carriage during unloading

In summary, the total cost of product damage occurring during the delivery and transportation process can be expressed as:

$$C_5 = C_{51} + C_{52} + C_{53} = \sum_{k\in K}\sum_{i\in N}(y_{ki}pq_i(\vartheta + 2e^{-\partial_1 t_0} - ge^{-\partial_1(t_{ki}+t_0)} - ge^{-\partial_2(s_{ik}+t_0)})) \tag{13}$$

(6) Carbon Emission Costs

The carbon emission costs of electric refrigerated vehicles consist of two parts: the carbon emissions generated during vehicle charging, and the emissions produced from the manufacture of materials required for maintenance and upkeep.

$$C_6 = C_{use} + C_p \tag{14}$$

$$C_{use} = \frac{(FC \times \frac{d_{ij}}{100})}{\mu} \cdot k \cdot C_{tax} \tag{15}$$

$$C_p = \sum m_i \bullet k_i \tag{16}$$

Here, FC represents the electricity consumption of the electric refrigerated vehicle per 100 kilometers, μdenotes the charging efficiency, and k is the carbon emission factor for the electricity consumed. mi indicates the mass of material i that needs replenishing, and ki represents the carbon emission factor associated with the use of material i.

2.4 Model Establishment

Objective function:

$$\min Z = C_1 + C_2 + C_3 + C_4 + C_5 + C_6 \tag{17}$$

Constraints:

$$\sum_{i \in K} q_{ik} \le Q_{\max} \qquad (k \in K) \tag{18}$$

$$\sum_{k \in K} \sum_{i \in N} x_{ijk} = 1 \qquad (j \in N) \tag{19}$$

$$\sum_{k \in K} \sum_{j \in N} x_{ijk} = 1 \qquad (i \in N) \tag{20}$$

$$\sum_{i \in 0} x_{ijk} = \sum_{j \in 0'} x_{jik}, \quad (i \in 0, j \in 0', k \in K) \tag{21}$$

$$Q_{0k} = Q_{\max}, \qquad (k \in K) \tag{22}$$

In the model described above, Equation (18) specifies that the total load of the electric refrigerated vehicle must be less than its maximum carrying capacity. Equations (19) and (20) ensure that each customer is served by only one refrigerated vehicle. Equation (21) indicates that the electric vehicles depart from the distribution center and eventually return to it. Equation (22) stipulates that vehicle k starts its route from the distribution center with a full battery.

3 ALGORITHM DESIGN

This paper addresses the fresh food logistics delivery problem by considering a variety of factors including costs and carbon emissions, and proposes an effective optimization solution for distribution. In order to solve the problem of premature convergence of PSO, the hybrid binary method is used to generate high quality initial solution, and then the hybrid particle swarm optimization strategy (GA-PSO) combined with genetic algorithm is introduced to enhance the search efficiency and optimization performance. Specific operations are as follows:

Step1: Mixed binary method generates the initial solution. Greedy algorithm: Each step selects the point that has the least impact on the total cost as the next delivery customer point. Neighborhood search: After defining the neighborhood structure, the search begins, and the local search is carried out systematically in the current neighborhood to find the optimal solution. Finally, the solutions of the above algorithms are sorted, and the three solutions with the best quality are selected as the initial solutions.

Step2: Introduce a good solution. The excellent solution of hybrid binary method is taken as the initial solution of particle swarm optimization algorithm. Each particle represents a distribution path, and its position vector is composed of customer points, and the velocity vector is initialized for each particle.

Step 3: Fitness Calculation. For each particle, the fitness function is defined as the sum of fixed costs, transportation costs, time window penalty costs, refrigeration costs, product damage costs, and carbon emission costs, with the objective to minimize this total sum.

$$f = \frac{1}{\min Z} \tag{23}$$

Step 4: Update Individual and Global Best Solutions. Individual best update: If the current fitness of a particle is better than its historical best fitness, then update its individual best solution. Global best update: Identify the best solution from all individual bests of the particles and update the global best solution.

Step 5: Hybrid Operations. In the route optimization problem, the fitness function may have multiple local optima, making PSO susceptible to getting trapped in these local optima. By introducing adaptive crossover and mutation strategies, the algorithm can increase the diversity of the population when necessary, thereby improving the probability of finding the global optimum. The specific formulas for crossover and mutation are as follows:

$$P_c = P_{c,base} + (1 - P_{c,base}) \times \frac{n_s}{n_m} \tag{24}$$

$$P_m = P_{m,base} + (1 - P_{m,base}) \times \frac{n_s}{n_m} \tag{25}$$

Here, Pc,base and Pm,base are the base crossover and mutation rates, respectively. ns and nm represent the number of stopping iterations and the maximum number of iterations, respectively.

Step 6:Velocity Update. In addition to the standard velocity updating, a dynamic inertia adjustment strategy is employed.

$$v_i^{(t+1)} = w \cdot v_i^{(t)} + c_1 \cdot r_1 \cdot (p_{best}, i - x_i^{(t)}) + c_2 \cdot r_2 \cdot (g_{best} - x_i^{(t)}) \tag{26}$$

$$w = w_{\max} - (w_{\max} - w_{\min}) \times \frac{I_c}{I_m} \tag{27}$$

Here, w is the inertia weight, with wmax and wmin representing the maximum and minimum values of the inertia weight, respectively. Ic and Im)are the current iteration number and the maximum number of iterations, respectively. c1and c2 are the learning factors, and r1 and r2 are random numbers.

Step 7: Position Update. Ensure that the route optimization remains within permissible limits.

$$x_i^{(t+1)} = x_i^{(t)} + v_i^{(t+1)} \tag{28}$$

Step 8: Termination Condition. Check whether the maximum number of iterations or other termination conditions have been reached. If the termination conditions have not been met, return to Step 2.

Step 9: Output the Optimal Solution. Output the best delivery route solution, which minimizes the total sum of fixed costs, transportation costs, time window penalty costs, refrigeration costs, product damage costs, and carbon emission costs.

4 EXPERIMENTAL SIMULATION AND RESULTS ANALYSIS

4.1 Experimental Case Study

In this study, we utilize the Solomon benchmark dataset to test the effectiveness and efficiency of the proposed algorithm. Specifically, we selected three instances that represent different delivery scenarios: C107, R105, and RC201. To set up experimental cases, we chose a subset of delivery points from each instance for analysis. This selection strategy aims to demonstrate the broad applicability and flexibility of our algorithm in handling various types of delivery routes—C-type for clustered routes, R-type for random routes, and RC-type for a combination of both. By testing on these classic experimental cases, our goal is to comprehensively evaluate the performance of the algorithm in practical use, particularly in terms of route optimization and cost reduction.

4.2 Algorithm Parameters.

In this study, we combine a hybrid Particle Swarm Optimization strategy with Genetic Algorithms, with the following specific parameters: Number of particles N = 50, Learning factor 1 c1=2.05, Learning factor 2 c2=2.05, Inertia weight =0.9, Population size m=60, Crossover rate (Pc)=0.7, Mutation rate（Pm）=0.05, Number of iterations G=50.

4.3 Model Parameters

The model parameter Settings are shown in the following table.

Table 2. Model parameter table

Argument	Numerical value	Argument	Numerical value
A	1	m_2	100RMB/vehicle
N	20	k_i	2.50RMB/kg
Q_{max}	1100kg	∂	0.05
V_k	50km/h	u_1	20RMB/h
m_1	500RMB/vehicle	u_2	15RMB/h

4.4 Algorithm Analysis

To comprehensively validate the performance of the proposed improved algorithm, this study will conduct in-depth testing on three carefully selected instances from the Solomon dataset: C107, R105, and RC201. We will primarily focus on the optimal solutions achieved by the algorithm and the number of iterations required to reach these solutions. The specific data are presented in the table below:

Table 3. Algorithm comparison table

Data set	Standard particle swarm optimization algorithm			Improved particle swarm optimization algorithm		
	Optimal solution	Mean solution	Mean frequency of convergence	Optimal solution	Mean solution	Mean frequency of convergence
C107	4678.9	4735.23	46.87	4047.34	4177.89	27.63
R105	4866.73	4855.74	58.65	4287.65	4365.57	32.49
RC201	4933.78	5035.83	65.33	4356.23	4472.81	39.85

4.5 Cost Analysis

In conducting a cost analysis of the logistics delivery system, this study will focus on comparing two different delivery modes: electric vehicle mode and traditional fuel vehicle mode. The purpose of this analysis is to delve deeper into the differences between these two modes in terms of transportation costs and carbon emissions. Figures 2 to 4 present the optimal route maps for electric vehicle mode under scenarios C107, R105, and RC201, each with 30 selected customer points.

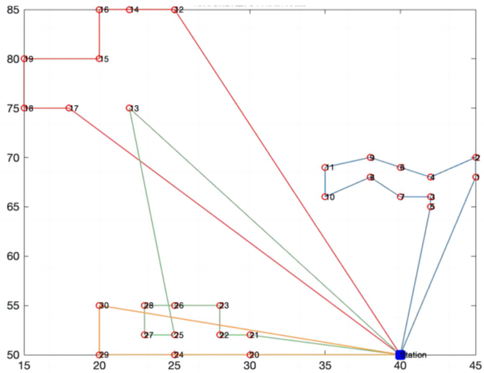

Fig. 2. C107 Optimal roadmap

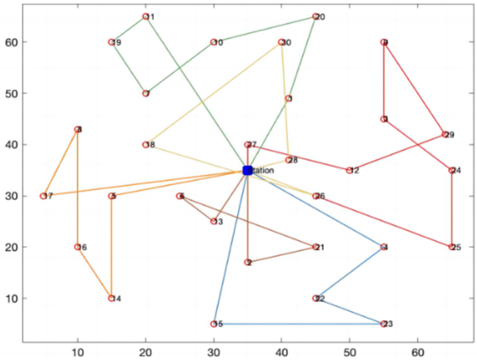

Fig. 3. R105 Optimal roadmap

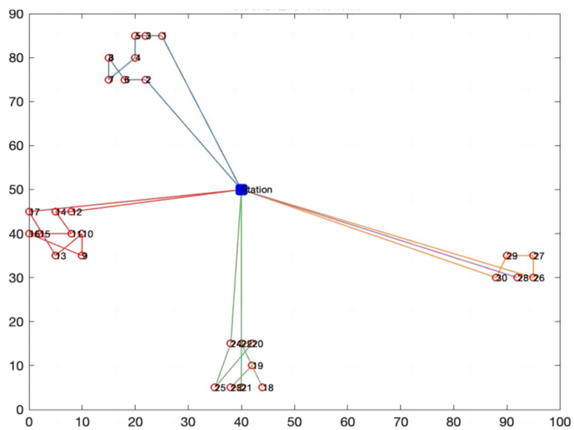

Fig. 4. RC201 Optimal roadmap

According to Table 4, compared to traditional fuel vehicle fleets, the total costs under the pure electric vehicle delivery mode have significantly decreased, with reductions of 13.35%, 16.95%, and 19.66% across the three datasets, respectively. In terms of environmental impact, carbon emissions are also lower in the pure electric vehicle mode than those of fuel vehicle fleets, with reductions of 44.34%, 43.53%, and 40.98%. Additionally, due to the efficiency of collaborative delivery, penalties for time window violations decreased by 46.30%, 24.01%, and 20.54%, respectively.

Analyzing the results of these experiments, the delivery mode combining drones with electric vehicles demonstrates outstanding performance in reducing delivery costs and carbon emissions through its efficiency, flexibility, and eco-friendly approach. This model leverages the advantages of drones for direct delivery of goods and the efficient energy conversion characteristics of electric vehicles, effectively avoiding traffic congestion and unnecessary long-distance transport. This greatly enhances delivery efficiency and reduces energy consumption.

Table 4. Comparative statement of costs

Data set	Fuel fleet			Electric fleet		
	Total cost	Carbon emission	Time window penalty	Total cost	Carbon emission	Time window penalty
C101	2832.68	194.65	264.43	2454.62	108.34	136.62
R101	3425.89	228.67	248.62	2845.32	129.11	188.92
RC101	3267.45	224.67	230.89	2625.17	132.59	183.47

5 CONCLUSIONS

This study comprehensively considers multiple factors such as transportation costs, carbon emissions, refrigeration effects, goods damage, and time window constraints. It constructs an optimization model with the objective of minimizing total costs and solves it using an improved particle swarm algorithm. Experimental results validate the effectiveness of the model and algorithm, demonstrating significant advantages of using electric vehicles for fresh produce delivery in reducing total costs, decreasing carbon emissions, and improving delivery efficiency. Compared to traditional fuel-based delivery modes, the electric vehicle mode achieves an average reduction of 14.52% in total costs and a 41.15% decrease in carbon emissions across different datasets. Additionally, the penalty for time window violations decreases significantly by an average of 30.83%. These findings not only confirm the dual advantages of the electric vehicle delivery mode in terms of economic and environmental benefits but also highlight its potential in enhancing logistics efficiency and customer satisfaction. Future research could further explore the adaptability and optimization strategies of this mode in different geographical environments and scales, providing theoretical and practical support for the low-carbon transformation of the logistics industry..

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