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Low-Carbon Logistics Distribution Vehicle Routing Optimization Based on INNC-GA

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Abstract: In order to tackle the issue of carbon emissions in logistics and distribution, a vehicle routing model was proposed with the aim of minimizing the overall cost, which includes the vehicle's fixed cost, transportation costs, and carbon emission costs. An enhanced genetic algorithm, based on a modified Nearest Neighbor Construction (NNC) method, was developed to solve this model. A comparative analysis was conducted using the Solomon dataset to study the impact of carbon emissions on vehicle routing optimization, comparing scenarios with and without considering carbon emission costs. The research findings revealed that the Improved NNC (INNC) method exhibited faster convergence compared with the random generation and random insertion methods. Despite a slight increase of 0.5127% in transportation cost when factoring in carbon emission costs, there was a decrease of 4.6914% in carbon emission costs and 0.3578% in total cost. These results offer theoretical insights and empirical evidence to inform the development of models for the logistics industry in the context of a low-carbon economy.

Keywords: low carbon logistics; genetic algorithm; vehicle path optimization; nearest neighbor algorithm

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1. Introduction

The rise of e-commerce and the global economy has highlighted the critical role of logistics and distribution in urban settings. However, the operation of vehicles in logistics not only contributes to traffic congestion in cities but also leads to significant carbon emissions, posing a serious threat to the environment. Currently, vehicle exhaust emissions are a major contributor to greenhouse gases on a global scale. Addressing the urgent need to reduce energy consumption and carbon emissions in logistics is paramount. The issue of green vehicle routing, aimed at minimizing energy consumption and carbon emissions, has emerged as a prominent topic in this domain.

Domestic and international research on vehicle routing optimization problems predominantly centers around three key aspects: vehicle routing problems with time windows [1–3], vehicle routing problems involving capacity constraints [4–7], and dynamic vehicle routing problems [8–10]. However, there is a lack of comprehensive studies that simultaneously address time window constraints, vehicle load constraints, and speed constraints in vehicle routing problems. As environmental concerns gain more attention, the inclusion of carbon emissions in vehicle routing problems, known as green vehicle routing problems, is emerging as a popular research area. Qiao et al. [11] conducted a comprehensive analysis of the social, economic, and environmental impacts, proposing an optimization model that minimizes total costs, including fixed vehicle costs, fuel costs, carbon emissions costs, and penalty costs. They utilized particle swarm optimization and taboo search algorithms to find a balanced solution that considers economic, social, and environmental factors. Qiu et al. [12] and Li et al. [13] developed heterogeneous vehicle routing models that incorporate carbon emissions costs and multi-vehicle type routing models aimed at minimizing total distribution costs while maximizing customer satisfaction. Their use of improved hybrid genetic algorithms and simulated annealing algorithms yielded valuable insights for optimizing the distribution of fresh agricultural products. Li et al. [14] and Zhou et al. [15] focused on constructing garbage vehicle routing optimization models within a low-carbon environmental protection framework, offering solutions to the challenges of the efficient collection and low-carbon transport of urban household waste. Guo et al. [16] established a dynamic vehicle routing optimization model and applied an enhanced traditional Dijkstra algorithm to solve it, demonstrating the practical significance of a dynamic vehicle routing model that accounts for carbon emissions. Their research not only provides important research results for and insights into the fields of green logistics and environmental protection but also offers innovations in theories and methods. It plays a positive role in various aspects of operational management and service quality for logistics enterprises, providing important references and guidance for businesses in the development of green logistics and environmental protection.

The current methods for solving vehicle routing problems mainly consist of exact algorithms and heuristic algorithms. Exact algorithms, such as branch and bound and dynamic programming, are typically used for small-scale problems to find the optimal solution. On the other hand, heuristic algorithms, including genetic algorithms, ant colony algorithms, taboo search algorithms, and simulated annealing algorithms, are more suitable for large-scale problems as they can quickly find near-optimal solutions. For instance, Zhang et al. [17] developed an improved multi-objective genetic algorithm based on Pareto optimality for a logistics distribution routing model with low-carbon and stochastic demand. Xu et al. [18] integrated the adaptive large neighborhood search algorithm with a genetic algorithm to create an Adaptive Large Neighborhood Search Genetic Algorithm (ALNSGA) for vehicle routing models in low-carbon cold chain logistics. Sun [19] and Zhu [20] combined a genetic algorithm with a large-scale neighborhood search algorithm, introducing the concept of destruction and repair to prevent genetic algorithms from getting trapped in local optima easily. They successfully solved vehicle routing models for low-carbon logistics distribution and cold chain logistics distribution, respectively. Additionally, Zhang et al. [21] developed an improved genetic algorithm and formulated a dynamic vehicle routing model that considers the impact of carbon emissions, demonstrating the algorithm's effectiveness through simulation testing. These studies demonstrate the wide application of genetic algorithms in the field of vehicle path optimization, solving complex vehicle path optimization problems and providing useful references and insights for environmentally sustainable development and improving transport efficiency.

In summary, although genetic algorithms are relatively well-established in the research for solving such problems, they still suffer from the problem of slow convergence. In addition, the existing research results on green vehicle path problems rarely have vehicle path objective models that consider time window constraints, vehicle loading constraints, and low carbon constraints in an integrated manner. Therefore, the purpose of this paper is to study the vehicle path model with the objective of minimizing the total cost of the vehicle fixed cost, transportation costs, and carbon emission costs, and to consider the effects of vehicle loading constraints and time window constraints on the total distribution cost to establish a low-carbon logistics and distribution model that considers the time window constraints. A further objective is to perform simulation operations on the model by designing a genetic algorithm that improves the minimum-cost-nearest-neighbor method, hoping to provide new ideas and new solutions for research in the fields of sustainable development and environmental protection, while providing logistics companies with more optimized and environmentally friendly distribution solutions, thus promoting the sustainable development of low-carbon logistics.

2. Problem Description and Basic Assumptions

This study explores the vehicle routing problem in the context of low-carbon logistics and distribution. The scenario involves a logistics center overseeing a fleet of vehicles responsible for delivering goods to multiple customers. Customer demand and locations are predetermined, with time window requirements. The goal is to minimize vehicle and carbon emission costs while meeting operating time window, vehicle load, and travel speed constraints. The following assumptions are made for analytical and research purposes:

(1) The distribution center's location is predetermined, with all vehicles originating from and returning to this center upon task completion.
(2) The types of vehicles in the distribution center are indistinguishable.
(3) The requirements of each customer are known, and all are within the maximum load capacity of the vehicle.
(4) It is strictly forbidden to violate the customer's time window and it is required that the delivery must be completed within the time window.
(5) The weight of the cargo in each vehicle must not exceed its maximum load capacity.
(6) Each customer should be served by a single vehicle, without any overlap.
(7) The vehicles travel at a fixed speed, regardless of factors such as traffic congestion or environmental conditions.

For clarity, Table 1 offers an explanation of the symbols utilized in the model.

Table 1. Description of symbols.

Symbol	Definition
N	Node combination, $N = \{0, 1, 2 \ldots .n\}$, where 0 is the distribution center and $1 - n$ are customer points
A	Arc set, $A = \{(i,j) \mid i \neq j,\ i,j \in N\}$.
K	Vehicle set, a total of K vehicles, $K = \{1, 2, \ldots .k\}$.
d_{ij}	Distance between node i and node j.
Q	The nominal capacity of the vehicle.
q_i	Demand of customer point i.
t_{ij}	The time taken by the vehicle to travel from node i to node j.
h_{ik}	The moment when vehicle k arrives at customer point i.
s_{ik}	The duration vehicle k stays at customer point i.
w_{ik}	The waiting time of vehicle k after reaching customer point i.
a_i	The earliest time a customer can be served.
b_i	The latest service time a customer can receive.
$[a_i\ b_i]$	Time window of the customer.
f_k	Vehicle fixed cost.
c_k	Unit transport cost of vehicle k.
δ	CO_2 emission factor.
F_e	Fuel consumption per kilometer.
E_c	Carbon emissions per kilometer.
E	Cost of carbon emissions.
P_0	Fuel consumption per unit distance when empty.
P_1	Fuel consumption per unit distance when fully loaded.
c_m	Cost of carbon emissions per unit.
y_{ik}	Customer i is serviced by vehicle k.
Description of symbols	
x_{ijk}	Vehicle k travels between nodes i and j.

3. Model Construction

3.1. Distance Calculation Method

In our study, in order to simplify the analysis and better focus on the core issue of the vehicle path problem, we assume that the vehicle travelling speed is constant, and do not take into account the influence of traffic congestion and other external environments. Based on this assumption, we chose Euclidean distance as the method to calculate the distance between customer points.

Euclidean distance is a straight-line distance between two points, it is the simplest and most intuitive distance measure, and due to the universality and simplicity of Euclidean distance, the algorithm using it as a distance measure can be more easily accepted and adopted by other researchers. Supposing there are two points, and the coordinates of point

A are (x_1, y_1) and the coordinates of point B are (x_2, y_2), then the Euclidean distance d between these two points can be calculated by using Equation (1):

$$d = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \tag{1}$$

3.2. Construction of the Model

The model developed in this study aims to minimize vehicle fixed costs, transportation costs, and carbon emission costs, taking into account time window constraints, vehicle load constraints, and speed constraints. Based on the notation provided, the low-carbon logistics and distribution path model considering time windows is formulated as follows:

$$\min T = \sum_{i=1}^{N}\sum_{j=1}^{N}\sum_{k=1}^{K} x_{ijk} d_{ij} c_k + \sum_{j=1}^{N}\sum_{k=1}^{K} y_{ojk} f_k + c_m F_e \delta \sum_{i=1}^{N}\sum_{j=1}^{N}\sum_{k=1}^{K} x_{ijk} d_{ij} \tag{2}$$

Equation (2) defines the objective function, which includes the vehicle fixed cost, vehicle travel cost, and carbon emission cost. The vehicle fixed cost is composed of vehicle maintenance, transfer, and workers' wages, with each vehicle being accounted for with a driver. The vehicle travel cost accounts for expenses incurred during the vehicle's journey.

Carbon emissions result from fuel consumption during vehicle travel. The logistics distribution model in this study focuses on path length and cargo weight. To simplify fuel consumption analysis, the study utilizes the load estimation method from literature [22]. This method considers fuel consumption per unit distance F_e as a linear function of the vehicle load q, that is

$$F_e = \frac{P_0}{P_1} q_{ij} + P_0 \tag{3}$$

And the relationship between fuel consumption and carbon emissions is

$$E_c = \delta \times F_e \tag{4}$$

Then the cost of the carbon emissions produced by the vehicle during transport is

$$E = C_m \times \delta \times F_e \tag{5}$$

Constraints are

$$\sum_{k=1}^{N}\sum_{j=1}^{K} x_{ijk} = 1 \quad \forall i \in N \backslash \{0\} \tag{6}$$

$$\sum_{k=1}^{K}\sum_{j=1}^{N} x_{ijk} = 1 \quad \forall j \in N \backslash \{0\} \tag{7}$$

Equations (6) and (7) indicate that only one vehicle can perform the delivery service at a customer point and only once.

$$\sum_{i=1}^{N}\sum_{k=1}^{K} x_{oik} = \sum_{j=1}^{N}\sum_{k=1}^{K} x_{ojk} \le k \tag{8}$$

Equation (8) illustrates that the transport vehicle initiates its journey from the distribution center, fulfills the distribution task, and ultimately returns to the same distribution center.

$$\sum_{i=1}^{N}\sum_{j=1}^{N} x_{ijk} \le Q \quad \forall i, j \in N \backslash \{0\} \tag{9}$$

Equation (9) indicates that the vehicle capacity limits.

$$\sum_{j}^{N} x_{oik} \leq 1 \quad k \in K \tag{10}$$

Equation (10) indicates that there is only one circuit per vehicle and no sub-circuits.

$$h_{ik} \leq b_i \quad \forall i \in N \tag{11}$$

Equation (11) indicates that the customer point must be reached before the latest time the customer can receive service.

$$a_i \leq w_{ik} + h_{ik} \leq b_i \quad \forall i \in N, k \in K \tag{12}$$

Equation (12) specifies that the service time must fall within the customer's designated time window.

$$t_{ij} + w_{ik} + h_{ik} + s_{ik} + H\left(1 - x_{ijk}\right) \leq h_{ik} \quad \forall i, j \in N, k \in K \tag{13}$$

Equation (13) indicates that the service time of both the front and back customers must satisfy their respective time window constraints.

$$x_{ijk} = \begin{cases} 1 \; vehicle\ k\ travelling\ from\ node\ i\ to\ node\ j \\ 0 \; if\ not \end{cases} \tag{14}$$

$$y_{ik} = \begin{cases} 1 \; customer\ i\ has\ vehicle\ k\ delivery \\ 0 \; if\ not \end{cases} \tag{15}$$

Equations (14) and (15) are decision variables, where i and j are arbitrary customer points, and k is an arbitrary vehicle.

4. INNC-GA

4.1. INNC

The minimum cost Nearest Neighbor Algorithm (NNC) is utilized in vehicle routing problems to produce high-quality feasible solutions. This paper introduces an enhanced version of NNC, called Improved NNC (INNC), specifically tailored to the Vehicle Routing Problem with Time Windows (VRPTW). The key steps for enhancing NNC are outlined as follows:

Step 1: Determining the distance from each customer point to the distribution center and selecting the point with the shortest distance as the initial customer on the vehicle route.

Step 2: Calculating the distance between the remaining customer points and the last customer point in the current path, arranging them in ascending order, and assessing whether the vehicle load constraints and customer time window constraints are met after insertion, then selecting the customer point with the most advanced order that satisfies the constraints to be inserted into the current path.

Step 3: Repeating Step 2; if no customer point meets the conditions, an additional vehicle is dispatched. If all customer points have been visited, the calculation process concludes.

4.2. GA

Genetic Algorithm (GA) is an evolutionary algorithm that utilizes a population of potential solutions to a problem. Individuals within the population are selected based on their fitness levels, undergo genetic operators such as crossover and mutation, and produce a new set of solutions. This process is repeated iteratively until an optimal solution is reached. The key terms associated with GA are explained as follows:

(1) Chromosome: The genetic makeup of an individual. A population consists of multiple chromosomes.

(2) Bit string: A representation of an individual, similar to a chromosome in natural genetics.
(3) Gene: A specific position within a chromosome that corresponds to a characteristic or variable of the solution.
(4) Individual: A solution represented by a chromosome in a genetic algorithm.
(5) Fitness: A measure of an individual's performance in solving a problem. It is used to assess the strengths and weaknesses of individuals and aid in selection.
(6) Genotype: The composition of genes on an individual's chromosome. It serves as the encoded representation of the individual within a genetic algorithm.
(7) Phenotype: The observable trait or characteristic displayed by an individual in the external environment. In genetic algorithms, the phenotype corresponds to the specific solution or characteristic encoded by the genotype.

4.3. INNC-GA

In some instances, when implementing a genetic algorithm, the conventional NNC method is used to start the population. Despite multiple generations of iteration, the constraints continue to be violated, preventing the attainment of the optimal solution. To tackle this challenge, a modification is made to the traditional NNC method, resulting in the introduction of the INNC method for initializing the genetic algorithm population. The workflow diagram of the INNC-GA can be seen in Figure 1.

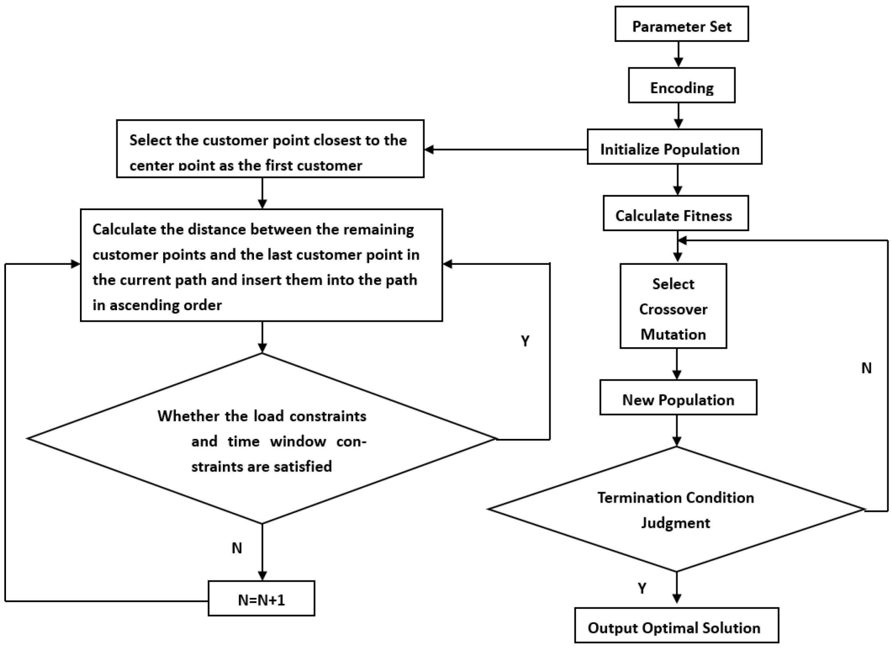


Figure 1. Workflow diagram.

(1) Coding

Common chromosome encoding methods include binary encoding, decimal encoding, integer encoding, etc. Because integer encoding directly represents the order in the path using integers, it is easier to understand and implement, and is more advantageous for solving vehicle routing problems. In this paper, integer encoding is used to encode the chromosome. Assuming the number of customers to be served is N and the maximum number of vehicles used by the distribution center is K, where 0 represents the distribution center, the chromosome length is N + K−1. For example, if a chromosome is given as 0 5 3 6 7 0 1 2 8 9 0, it represents the following:

Path 1: 0-5-3-6-7-0,
Path 2: 0-1-2-8-9-0.

(2) Initialization of the population

In genetic algorithms, population initialization is a critical factor that influences the algorithm's performance and convergence speed. Two important considerations in population initialization are determining the population size and generating initial solutions. The choice of population size significantly impacts the algorithm's performance. A larger population size in a complex solution space usually results in higher diversity within the population but requires more computational resources. On the other hand, a smaller population size may lead to premature convergence, trapping the algorithm in a local optimum. The initial solutions are crucial for initializing the population. This study utilizes the Improved Nearest Neighbor Chain (NNC) algorithm to generate a set of high-quality feasible solutions, aiming to enhance the quality and feasibility of the initial population and improve the overall performance of the genetic algorithm.

(3) Fitness Function

The fitness function is a key determinant of an individual or solution's quality, playing a vital role in selecting individuals with higher evolutionary potential. This process directs the algorithm towards achieving a better solution for the problem at hand. In the context of the vehicle routing problem with time windows, it is essential to adhere to time window constraints. To tackle the risk of violating these constraints, a penalty function is used in this study to meet customer demands [19]. The formula for this penalty function is detailed below.

$$F = T + mq(s) + nw(s) \tag{16}$$

where F is the penalty function, T is the total cost incurred in the distribution process, $q(s)$ is the sum of load constraints violated for each path, and $w(s)$ is the sum of time window violations. n is set to be larger, and m is set to be relatively small because the VRPTW problem is more likely to violate time window constraints than load constraints.

The advantage of the objective function utilized in this study lies in its ability to minimize total distribution costs, resulting in a more efficient path. During the selection process, it is crucial to assess the level of adaptation and prioritize individuals with a higher degree of adaptation. As a result, this paper defines the degree of adaptation as the inverse of the penalty function. Consequently, as the objective function decreases (indicating lower distribution costs), the degree of adaptation increases, and vice versa. Put simply, individuals with lower objective function values demonstrate greater degrees of adaptation and are more likely to be chosen. The fitness function can be mathematically represented as follows:

$$Fit(j) = \frac{1}{F} \tag{17}$$

(4) Selection

The selection operation aims to steer the algorithm towards an exceptional problem solution by considering the fitness of each individual. In this study, the proportional selection method is employed to choose the parent individual, wherein the probability of an individual being selected is directly proportional to its fitness function value. The selection probability ($P(i)$) for the ith individual is calculated as follows:

$$p(i) = \frac{Fit(i)}{\sum Fit(i)} \tag{18}$$

(5) OX Crossover

OX crossover is a widely used crossover operation in genetic algorithms, which generates two offspring individuals from two parent individuals, thereby creating a new population. The underlying principle of OX crossover is illustrated in Figure 2.

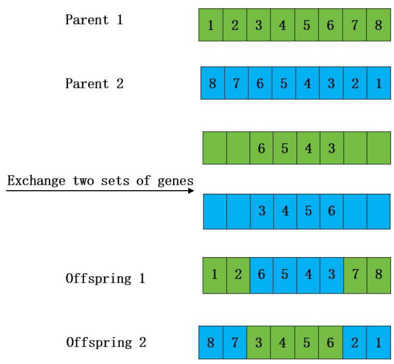


Figure 2. OX crossover basics.

(6) Mutation

The basic principle of mutation, shown in Figure 3, is the repair and replenishment of certain genes that may have been lost during crossover.

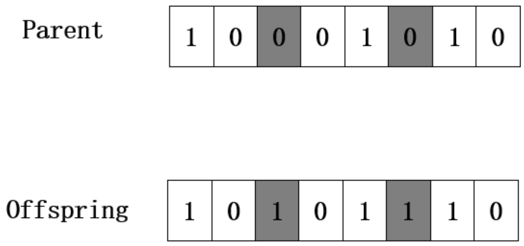


Figure 3. Basic principle of mutation.

The process of mutation involves selecting individuals from the current population, randomly choosing gene loci, and applying a specific mutation strategy to the selected gene loci. In Figure 2, genes 1 and 0 from the parent generation are mutated to genes 0 and 1, leading to the creation of a new offspring.

5. Comparison and Analysis of Experimental Results

5.1. Experimental Setup

The algorithm was tested using the Solomon test database, which includes three types of problems: C, R, and RC. For the purpose of evaluating the algorithm's performance, this study focused on six specific problems: C101, C201, R106, R206, RC108, and RC208. Each problem consisted of 100 customer demand points with coordinates, service time windows, service times, and demand values. The model parameters were determined based on the previous literature [19] and current traffic market conditions, as detailed in Table 2. Algorithms are written in MATLAB Version9.10(R2021a)and simulation experiments are performed.

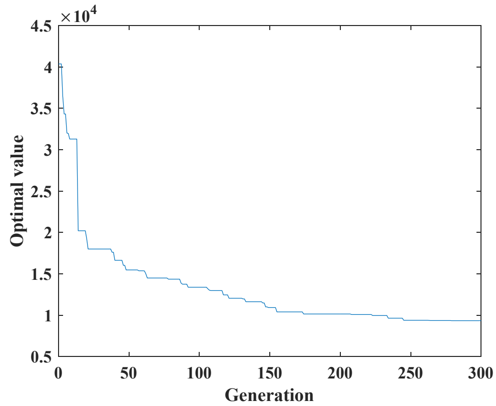
Table 2. Model parameters.

f_k	500	$NIND$ (Population size)	50
$c_k/(¥{\cdot}\text{vehicle}^{-1})$	0.8	$MAXGEN$ (Number of iterations)	300
$\delta/(¥{\cdot}\text{km}^{-1})$	2.63	p_c (Crossover probability)	0.9
$F_e/(\text{L}{\cdot}\text{km}^{-1})$	0.16	p_m (mutation probability)	0.05
Model parameters.			
$c_m/(¥{\cdot}\text{kg}^{-1})$	0.76	GAP (generation gap)	0.9
$cap/(\text{kg}{\cdot}\text{vehicle}^{-1})$	200	m (penalty coefficient)	100
$P_0/(\text{L}{\cdot}\text{km}^{-1})$	0.122	n (penalty coefficient)	500
$P_1/(\text{L}{\cdot}\text{km}^{-1})$	0.388		

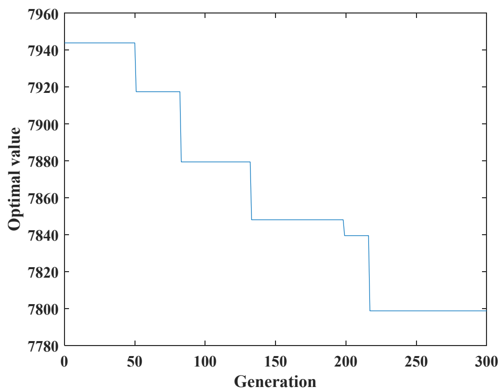
5.2. Effects of the Initial Solution

5.2.1. Speed of Convergence

In the study conducted on R206, 100 customer points were used as an example. Initial solutions were created through random generation, random insertion, and the INNC algorithm. The population size was set at 50 with 300 iterations. Figure 4 displays the optimal iteration graph of the model. Analysis of the graph reveals that the random generation method (RGM) stabilizes around the 282nd iteration, the random traversal insertion method (RTIM) stabilizes around the 217th iteration, and the INNC method stabilizes as early as the 103rd iteration. The INNC algorithm demonstrates faster convergence compared with the random generation and random traversal insertion methods. This is because the random generation method directly generates a certain number of individuals as an initialization population, and the genes of each individual are randomly generated without any specific law or order; the random traversal insertion method randomly selects an individual as a starting point in an empty population, and then randomly selects the next individual to be inserted into the population until the number of populations reaches a certain size, generating a complete path. In contrast, the INNC method is used to initialize the population, which generates the initialized population according to the characteristics and constraints of the problem, selects the customer closest to the distribution center as the starting point, then calculates the distance between the remaining customer points and the last customer point in the current path and arranges them according to the ascending method. It then determines whether the constraints are satisfied after insertion. Firstly, initializing the population in this way makes it able to directly generate feasible solutions that satisfy the constraints, making it faster to approach the optimal solution, which is conducive to the algorithm finding better solutions faster in the subsequent evolution process; secondly, under the premise of satisfying the constraints, it is able to select the customer point with the smallest insertion cost at each step, resulting in a better initial solution.

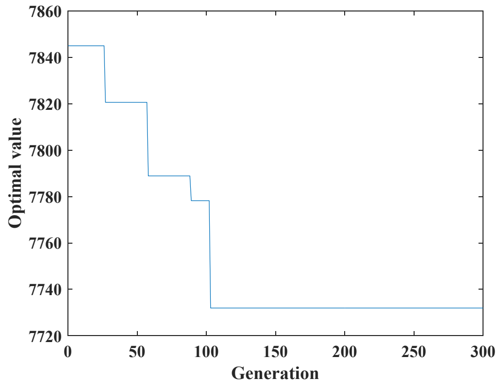


(**a**)



(**b**)

Figure 4. *Cont.*



(c)

Figure 4. Optimization process. (**a**) Random generation method; (**b**) Random traversal insertion method; (**c**) INNC.

5.2.2. Cost Distance

The results of each initial solution algorithm are presented in Table 3, with a comparison shown in Figure 5. Figure 5 clearly demonstrates that the INNC algorithm outperforms both the random generation method and the random traversal insertion method in terms of the number of vehicles used, transport distance, and total cost. By analyzing Table 3 and Figure 5, it is evident that the INNC algorithm achieves a 42.86% reduction in the transfer rate compared with the random generation method and an 11.11% reduction compared with the random traversal insertion method. Furthermore, the INNC algorithm shows a decrease in total transport distance by 34.87% compared with the random generation method and 15.03% compared with the random traversal insertion method, while also exhibiting a significantly faster running time. These results indicate that initializing the population with the INNC algorithm leads to significantly improved computational outcomes compared with the random generation and random traversal insertion methods. The INNC algorithm is shown to generate high-quality initial solutions, bringing it closer to the optimal solution and enhancing the algorithm's ability to search the solution space effectively, ultimately increasing the likelihood of finding a lower-cost optimal solution, speeding up convergence, and saving computational resources. In practical applications, the reduction of cost distance can, firstly, reduce the distribution cost, which will cause the logistics company to save costs and improve efficiency whilst operating; secondly, it can improve the distribution efficiency, which will cause the goods to be delivered to the destination faster, improving customer satisfaction; thirdly, it can reduce environmental pollution by reducing transport distance, so that the fuel and emissions of the corresponding reduction's impact on the environment is conducive to sustainable development.

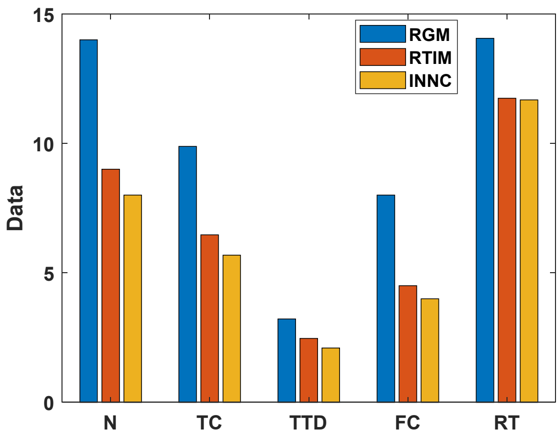


Figure 5. Comparison of results.

Table 3. Effect of the Initial Solution on the Genetic Algorithm.

Method	Number of Vehicles(N)	Total Cost (TC)	Total Transport Distance (TTD)	Fixed Cost (FC)	Running Time (RT)
RGM	14.00	9.88 K	3.22 km	8.00 K	14.06 s
RTIM	9.00	6.47 K	2.47 km	4.50 K	11.74 s
INNC	8.00	5.68 K	2.10 km	4.00 K	11.68 s

5.2.3. Feasible Solution Solving Speed

In the context of the vehicle routing problem with time window constraints, particularly when dealing with strict time window requirements, it can be challenging to identify feasible solutions for certain instances. In some scenarios, it may even be impossible to find a viable solution. This difficulty is primarily attributed to the large scale of certain instances and the stringent time windows, which make it challenging for algorithms to effectively optimize for both distance and time window constraints simultaneously. By employing random generation method, random traversal insertion, and the INNC algorithm to address the R206 instance, Table 4 showcases the constraint violations. The results indicate that the random generation method achieved a feasible solution without violating constraints by the 256th iteration, the random traversal insertion method found a feasible solution without constraint violations by the 3rd iteration, and the INNC algorithm consistently produced solutions that adhered to constraints from the initial iteration. This highlights that the INNC algorithm yields higher-quality initial solutions compared with the random generation and random insertion methods. At the same time, since the INNC algorithm finds a feasible solution that satisfies the constraints in the first generation, the algorithm does not need to spend time and resources searching and optimizing the solution space and can directly start the evolution process, which speeds up the convergence of the algorithm and makes the algorithm find a better solution faster; since it does not need to perform many iterations to search for a feasible solution, the computational cost and time consumption can be reduced, which is particularly important for large-scale problems and practical application scenarios with high real-time requirements.

Table 4. Constraint Violation.

	RGM	RTIM	INNC
The algebra of finding feasible solutions	256	3	1

In practice, for urgent or time-sensitive tasks, being able to quickly find a feasible solution will improve delivery efficiency and service quality; in the field of logistics and distribution, being able to quickly find a feasible solution that meets the constraints means reducing unnecessary waiting and planning time, which reduces costs. At the same time, finding a feasible solution quickly means that the delivery task can be completed more punctually, which improves customer satisfaction and confidence, which is very important for maintaining customer relationships and brand image. All of this is very beneficial for logistics companies.

5.3. Impact of Low Carbon Constraints

To further investigate the impact of carbon emissions on vehicle distribution paths and the performance of the INNC algorithm, this study focuses on the first 50 customer points from each of the six arithmetic sets: C101, C201, R106, R206, RC108, and RC208. Two scenarios are considered: one without considering carbon emission costs (referred to as X) and the other accounting for carbon emission costs (referred to as Y). Computational simulations are conducted, and the results are presented in Table 5. The comparative analysis is visualized in Figure 6. To enhance comprehension of cost variations, the increases and decreases of each arithmetic set are calculated separately, and their average values are used to represent the final outcome, as outlined in Table 6.

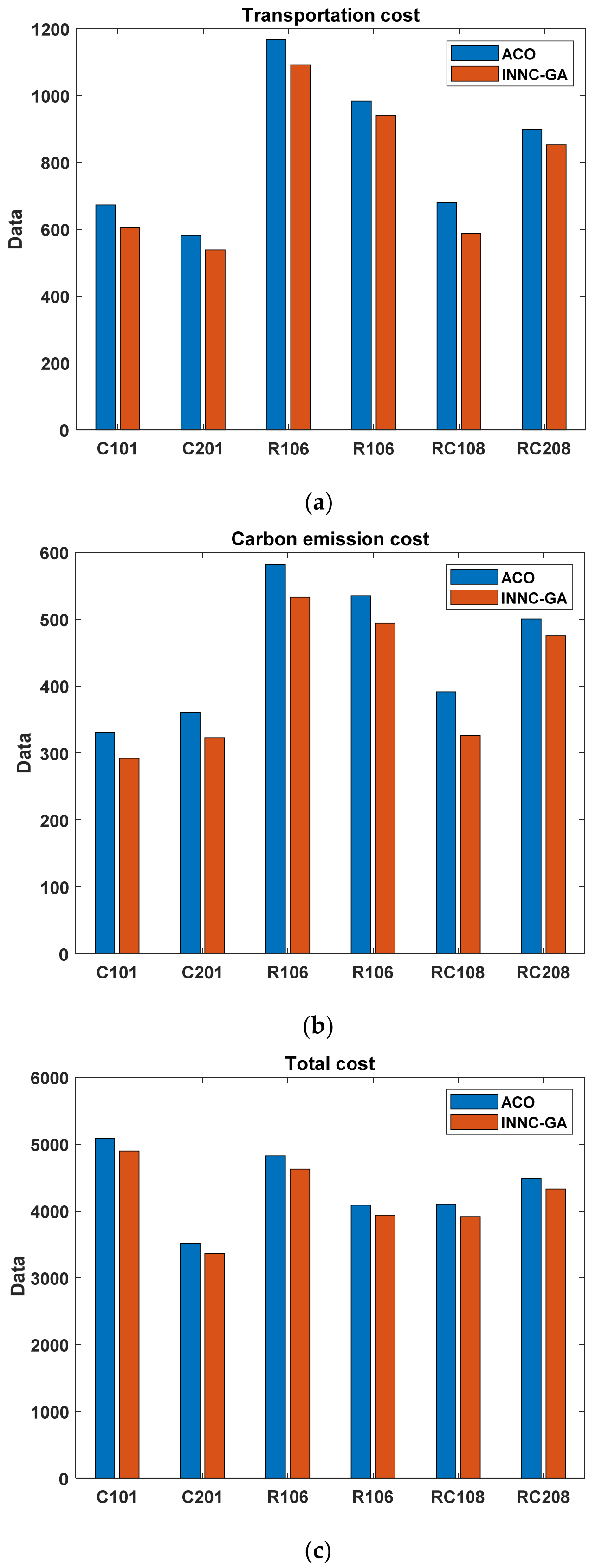


Figure 6. Comparison of results. (**a**) Transport cost; (**b**) Carbon emission cost; (**c**) Total cost.

Table 5. Solution results.

	Example Set	Number of Vehicles	Transportation Distance Cost	Total Cost	Carbon Emissions Cost
X	C101	8	600.0125	4917.2758	317.2633
	C201	5	536.1564	3379.4549	343.2985
	R106	6	1090.2500	4637.8854	547.6354
	R206	5	941.6520	3961.8207	520.1687
	RC108	6	576.5320	3930.2307	353.6987
	RC208	6	851.2321	4321.4887	470.2566
Y	C101	8	605.0063	4897.1749	292.1686
	C201	5	538.6560	3361.7812	323.1253
	R106	6	1092.2883	4625.2290	532.9406
	R206	5	941.7303	3935.9300	494.1998
	RC108	6	586.6879	3913.0429	326.3550
	RC208	6	852.7563	4327.9224	475.1662

Table 6. The reduction in cost for two models.

	Example Set	Reduction in Transportation Cost (%)	Reduction in Total Cost (%)	Reduction in Carbon Emissions Cost (%)
	C101	0.8323	−0.4088	−7.9097
	C201	0.4662	−0.5230	−5.8763
	R106	0.1869	−0.2729	−2.6833
	R206	0.0083	−0.6535	−4.9924
	RC108	1.7616	−0.4373	−7.7308
	RC208	−0.1791	0.1489	1.0440
Average		0.5127	−0.3578	−4.6914

(1) Comparison of solution results

The analysis of graph 6 reveals that incorporating carbon emission costs into the vehicle path optimization solution results in higher transport costs compared with solutions that do not consider carbon emissions. However, the carbon emission cost and total cost are notably lower than those of models that do not factor in carbon emissions. By examining Tables 4 and 5, the following conclusions can be derived:

(1) The results show that the inclusion of carbon emission costs in the target model leads to an average increase in transport costs of 0.5127%. However, there is a significant reduction of 4.6914% in the carbon emission cost and a reduction of 0.3578% in the total cost compared with the model without carbon emission costs. Cost reduction for logistics companies can firstly improve competitiveness: in a competitive market, cost advantage is an important factor in attracting and retaining customers; secondly, it can optimize operational efficiency: this helps to reduce wastage of resources, improve productivity, and enable logistics operators to run their business more efficiently; thirdly, it can reduce operational risk: cost control not only improves profitability, but also makes companies more risk resilient and able to cope with market fluctuations and uncertainties; fourthly, it is in line with regulatory requirements: many countries and regions have relevant environmental regulations that require companies to reduce carbon emissions, and logistics operators can better comply with regulations and legal issues. Overall, cost reduction plays an important role for logistics companies, so logistics operators should pay attention to cost control and environmental awareness to achieve better business results and social benefits.

(2) The target model after considering carbon emission costs reduces carbon emission costs, although the transport costs and transport distances increase. This not only helps logistics companies to achieve sustainable development by conserving resources and protecting the environment (companies can better meet future challenges and lay a solid foundation for long-term development) but also enhances brand image and reduces carbon emission costs by showing that companies are actively fulfilling their responsibility to

protect the environment, which helps to build a good corporate image and attract more environmentally conscious customers.

(2) Comparison of distribution paths

Using C201 as an example, we explore the variations in delivery routes for two objective models, as shown in Tables 7 and 8.

Table 7. Considering the cost of carbon emissions cost.

Number of Vehicles	Customer Points	Considering the Cost of Carbon Emissions Cost
1	10	0-22-24-33-31-35-37-38-9-11-10-0
2	13	0-5-2-1-7-3-4-40-44-46-45-50-43-8-0
3	9	0-6-32-49-47-42-41-48-0
4	11	0-20-30-29-34-28-26-23-18-19-15-25-0
5	7	0-27-39-36-16-14-12-17-13-21-0

Table 8. Without considering the cost of carbon emissions cost.

Number of Vehicles	Customer Points	Without Considering the Cost of Carbon Emissions Cost
1	10	0-50-45-44-40-49-46-41-42-43-48-0
2	13	0-6-31-34-35-39-38-37-36-29-27-22-21-8-0
3	7	0-32-33-28-26-23-30-24-0
4	11	0-25-18-19-16-14-12-15-17-13-9-20-0
5	9	0-47-4-3-7-1-2-10-11-5-0

A comparison of the delivery routes for the two objective models in Tables 7 and 8 reveals that the number of vehicles remains unchanged, and the majority of delivery routes are the same. Despite the high similarity in delivery routes between the two models, they exhibit significant differences in terms of carbon emission costs and total costs. In the objective model that considers carbon emissions, the average transportation cost increased by 0.5127%, while the carbon emission cost decreased by 4.6914%, resulting in an average reduction of 0.3578% in total costs, as shown in Table 6. This reduction may be attributed to the prioritization of serving customers with high demand and distant locations in the model considering carbon emission costs. Despite the increase in transportation costs, the decrease in carbon emission costs led to an overall cost reduction. The comparison of the models indicates that the vehicle routing model considering carbon emissions can effectively reduce both carbon emission costs and total costs. Furthermore, the improved genetic algorithm proposed in this study significantly impacts the resolution of vehicle routing problems related to carbon emissions.

5.4. Algorithm Comparison

The model proposed in this study aims to minimize the total cost of the vehicle fixed cost, transport costs, and carbon emission costs, and integrates the effects of time window constraints and vehicle load constraints on the total distribution cost. For the solution algorithms for this class of problems, studies have shown that the Ant Colony Algorithm (ACO) exhibits strong robustness and effectiveness. Therefore, in order to assess the performance difference between the algorithm designed in this study (INNC-GA) and the ACO algorithm in solving this type of problem, combined with the solution results of 5.3 for the model considering carbon emission cost, the ACO algorithm is used to simulate the six example sets of C101, C201, R106, R206, RC108, and RC208, respectively, with the specific comparison graphs shown in Figure 6. It can be seen that the INNC-GA algorithm designed in this study outperforms the ant colony algorithm in terms of transport cost, carbon emission cost, and total cost when satisfying the time window constraints and vehicle loading constraints. This indicates that the INNC-GA algorithm designed in this study has significant advantages in solving the vehicle path optimization problem with time window constraints, which can help logistics enterprises to reduce the cost expenditure, provide more environmentally friendly operations, and create greater economic and environmental benefits for the enterprises.

6. Conclusions and Outlook

This research examines a vehicle path optimization approach for low-carbon logistics while taking into account time window constraints. This study comprehensively analyzes the factors influencing time window constraints, vehicle load constraints, and speed constraints. A vehicle path optimization model is developed to minimize the total cost, incorporating the vehicle's fixed cost, transportation costs, and carbon emission costs. This study starts from the generation of initial solutions, without considering carbon emission costs, and then takes into consideration three aspects of carbon emissions costs in the analysis. To enhance the efficiency of the optimization process, an improved version of NNC's genetic algorithm was designed, and the following conclusions were obtained.

(1) The quality of the initial solution plays a crucial role in the efficiency of the genetic algorithm. The initial solution produced by the INNC method in this study can directly generate feasible solutions that meet the constraints and exhibit a quicker convergence speed.
(2) The results of the test cases demonstrate that the genetic algorithm with INNC initial population yields superior quality initial solutions compared with the random generation and random traversal insertion methods. Furthermore, it surpasses the random generation and random traversal insertion methods in vehicle utilization, total transport distance, total cost, and running time.
(3) The genetic algorithm with INNC initialization population is utilized to simulate and solve both the model without considering carbon emission costs and the model considering carbon emission costs. The results show that the model, when taking into account carbon emission costs, reduces the carbon emission cost and the total cost by an average of 4.6914% and 0.3578%, respectively, although the transportation cost increases by an average of 0.5127%. Therefore, the vehicle path model that considers carbon emissions can lower the carbon emission cost and the total distribution cost, aligning with the requirements of a low-carbon economy and offering a valuable foundation for decision-making in the logistics industry within a low-carbon economy.

Based on the limitations of this paper, further in-depth research can be carried out with regards to the following three aspects: (1) the model is simplified in this paper, and considering traffic congestion and mixed fleet vehicle path optimization models will be important research directions in the future; (2) this paper mainly focuses on the description of the research methodology and the results, so the search for a specific solution for the field of logistics under low-carbon emissions will be the next research focus; and (3) in the distance calculation, the actual road network is not taken into account, so how to incorporate the road traffic network and other practical factors into the model will be the focus of upcoming research.

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