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An improved discrete particle swarm optimization approach for a multi-objective optimization model of an urban logistics distribution network considering traffic congestion

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ABSTRACT

To optimize urban logistics networks, this paper proposes a multi-objective optimization model for urban logistics distribution networks (ULDN). The model optimizes vehicle usage costs, transportation costs, penalty costs for failing to meet time windows, and carbon emission costs, while also considering the impact of urban road traffic congestion on total costs. To solve the model, a DPSO (Discrete Particle Swarm Optimization) algorithm based on the basic principle of PSO (Particle Swarm Optimization) is proposed. The DPSO introduces multiple populations to handle multiple targets and uses a variable neighbourhood search strategy to improve the search ability of particles, which helps to improve the local search ability of the algorithm. Simulation results demonstrate the effectiveness of the proposed model in avoiding traffic congestion, reducing carbon emissions costs, and time penalty costs. The optimization comparison results between DPSO and PSO also verify the superiority of the DPSO algorithm. The proposed model can be applied to real-world urban logistics networks to improve their efficiency, reduce costs, and minimize environmental impact.

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1. Introduction

As urban populations continue to grow, the demand for urban logistics services has increased significantly. The logistics industry plays a crucial role in the economic development of cities [1-6]. However, the development of urban economies and the increase in private cars have led to increased traffic congestion, which has added pressure to the urban transportation network. Logistics companies must not only deal with traffic congestion during distribution, but also meet increasingly strict time requirements from customers. To meet the growing demand for timely delivery services under complex and unstable urban traffic conditions, logistics companies must find ways to provide efficient and effective distribution services that meet customer needs.

In the process of urban logistics distribution, the shortest distance between two customer nodes is often not the most efficient route, especially under urban traffic conditions where the shortest distance route is often the most congested. To avoid congested sections, shorten delivery times, and respond to customer time needs, logistics companies require an optimized distribution network. Improving the efficiency of logistics service delivery while meeting customer needs and ensuring customer loyalty can not only improve the core competitiveness of enterprises, but also alleviate urban traffic congestion and improve the urban environment.

In addition, environmental pollution caused by urban logistics activities has become a critical issue. Low-carbon logistics plays an important role in the low-carbon development of the environment and provides an essential guarantee for economic and social low-carbon development. Therefore, logistics companies must address the environmental problems caused by urban logistics activities. Green distribution is a necessary consideration for cities to optimize the overall logistics facility layout and distribution network. To optimize urban logistics networks, it is essential to consider both traffic congestion and green distribution, as it can improve the economic benefits of logistics enterprises while reducing the carbon emissions generated in the process of logistics distribution.

This paper proposes an urban logistics network optimization model that considers the impact of traffic congestion on urban logistics distribution. The model aims to minimize vehicle usage costs, transportation costs, time penalty costs, and carbon emission costs. To solve the model, we introduce an improved discrete particle swarm optimization (DPSO) algorithm that introduces multiple populations to handle multiple targets and uses a variable neighbourhood search strategy to enhance the search ability of particles and improve the local search ability of the algorithm. Simulation experiments verify the effectiveness of the proposed model and the superiority of the DPSO algorithm.

2. Literature review

The vehicle routing problem (VRP) is a fundamental problem in the optimization of urban logistics networks. Since its inception in 1945, numerous research studies have been published [7-15]. Gulczynski *et al.* [16] proposed a vehicle routing problem based on batch delivery and developed a heuristic method to solve the problem. Contardo and Martinelli [17] studied the multi-site vehicle routing problem with capacity and routing length constraints and designed a new exact algorithm to solve the problem. Bertazzi and Secomandi [18] focused on vehicle routing problems with random demand and replenishment and introduced a new method to approximate the expected cost of any VRPSD with replenishment.

In recent years, research on VRP has become more diverse, with scholars proposing models to optimize different aspects of logistics transportation. For example, Islam *et al.* [19] studied the Clustered Vehicle Routing Problem (CluVRP) and proposed a new hybrid meta-heuristic algorithm combining particle swarm optimization (PSO) and variable neighbourhood search (VNS) to solve the model. Solomon and Desrosiers [20] incorporated the concept of time windows into vehicle routing problems, and Jabali *et al.* [21] proposed a vehicle routing problem with soft and hard time windows. Rodríguez-Martín and Yaman [22] developed a periodic vehicle routing problem with driver consistency, and Yuan *et al.* [23] studied the generalized vehicle routing problem with time windows. Zhao *et al.* [24] considered the departure time and the distance between two customers. They proposed a bi-objective mixed integer linear model to optimize the total transportation cost and time cost.

The Green Vehicle Routing Problem has gained significant attention in recent years, aiming to promote green development by reducing energy consumption and carbon emissions in logistics activities. Scholars have proposed various models to optimize different aspects of logistics transportation while reducing carbon emissions. For example, Demir *et al.* [25] compared and analyzed six models for carbon emissions and energy consumption. Kirschstein and Meiselb [26] designed a comprehensive carbon emission calculation model by considering factors such as vehicle speed, load, and road conditions. Naderipur and Alinaghian [27] studied low carbon VRP with the goal of reducing vehicle energy consumption and carbon emissions. Kwon *et al.* [28] proposed a multi-vehicle VRP model based on carbon emissions to minimize total cost. Suzuki [29] established a VRP model aimed at minimizing energy consumption and carbon emissions. Li *et al.* [30] constructed a VRP model that aimed to minimize the sum of vehicle fixed usage costs, fuel consumption, and carbon emissions costs. Wen *et al.* [31] proposed a multi-site model of vehicle routing to optimize carbon emissions, fuel consumption, vehicle rental, and driver wage costs. They developed an improved adaptive large neighbourhood search (ALNS) algorithm to effectively solve the problem. Guo *et al.* [32] studied the multi-compartment vehicle routing problem considering carbon emissions and optimized the total transportation cost, including carbon emissions, using a three-dimensional ant colony optimization algorithm (TDACO). Li and Li [33] proposed a multi-objective supply chain network optimization model that aimed to optimize network costs, carbon trading costs, and customer satisfaction losses. They developed a new improved NSGA-II algorithm to solve the model. Zhu *et al.* [34] established a CVR for multiple warehouses with the goal of minimizing the carbon emissions of the fleet required to deliver the required goods to customers.

Despite the significant progress made in the field of the Green Vehicle Routing Problem, there is still a need for more effective and comprehensive models that can address the challenges posed by traffic congestion and low-carbon emission reduction in urban logistics network optimization. Therefore, this paper proposes a new model and algorithm to address these gaps in the literature, which has practical significance for the development of low-carbon logistics and the improvement of urban traffic congestion. Urban traffic networks have time-varying characteristics due to factors such as morning and evening traffic peaks, road speed limits, traffic regulations, and external accidents. To address this, some scholars have studied time-dependent vehicle routing problems (TDVRP) under time-varying road networks. For example, Jabbarpour *et al.* [35] established a TDVRP model that aimed to minimize driving time and fuel consumption, and designed different traffic congestion scenarios for experiments. Xiao and Konak [36] proposed that highway transportation companies can reduce their CO_2 emissions through effective vehicle routing and delivery schedules based on traffic congestion in their service areas. Poonthalir and Nadarajan [37] focused on behavior in variable speed environments and its impact on route costs and fuel consumption. They built a TDVRP model that aimed to minimize vehicle travel distance and fuel consumption and designed an improved particle swarm optimization algorithm to solve the problem. Çimen and Soysal [38] considered the vehicle routing problem under time-dependent and random vehicle speeds. The research results showed that incorporating vehicle speed randomness into the model enabled optimization of the final distribution route in terms of travel duration, carbon emissions, and travel costs. Ehmkea *et al.* [39] constructed a TDVRP model that aimed to minimize carbon emissions and solved it using a tabu search algorithm. Sarbijan and Behnamian [40] proposed that in the context of congestion in urban transportation networks, there is a higher requirement for fast, flexible, reliable, and low-cost delivery in urban areas. In real-time collaborative regional vehicle routing problems with flexible time windows, a combination of urban logistics transportation and distribution composed of various vehicles can reduce the number of times to return to physical warehouses, reduce costs, and save time.

Through a comprehensive literature review, scholars have proposed various models to address the challenges posed by time-varying road networks in urban logistics transportation. However, there is still a need for more effective and comprehensive models that can address the challenges posed by traffic congestion, low-carbon emission reduction, and time-varying road networks in urban logistics network optimization. Therefore, this paper proposes a new model and algorithm to address these gaps in the literature, which has practical significance for the development of low-carbon logistics and the improvement of urban traffic congestion. Through a comprehensive literature review, it was found that some research results have been generated on the Vehicle Routing Problem (VRP) under traffic congestion. However, the existing research is limited to constant vehicle speed, and there is a lack of research on VRP under time-varying road networks. Additionally, there is a shortage of research on the impact of traffic congestion and low-carbon emission reduction on urban logistics network optimization.

To address these gaps in the literature, this paper proposes a new multi-objective urban logistics network optimization model that considers traffic congestion to optimize vehicle usage costs, transportation costs, penalty costs, and carbon emission costs. The proposed model takes into account the impact of time-varying road networks and the need for low-carbon logistics. To solve the model, a DPSO algorithm based on the basic principle of PSO is developed.

This research has practical significance for the development of low-carbon logistics and the improvement of urban traffic congestion. By optimizing vehicle routing and reducing carbon emissions, this research can help reduce the negative impact of logistics activities on the environment and promote sustainable development. Moreover, the proposed model and algorithm can provide valuable guidance for logistics companies and transportation departments in urban areas to optimize their logistics network and reduce transportation costs.

3. Optimization model of vehicle routing problem in urban logistics distribution networks

3.1 Problem description

In today's low-carbon economic environment, it is crucial to consider not only conventional costs such as vehicle usage costs, transportation costs, and penalty costs for failing to meet the time window in urban logistics distribution but also the carbon emission costs associated with transportation. Additionally, the impact of urban road traffic conditions on total costs should also be considered. Therefore, this paper proposes a new model for the Vehicle Routing Problem (VRP) in Urban Logistics Distribution Networks (ULDN), which takes into account traffic congestion. The problem can be described as a distribution center providing logistics distribution services to multiple customer points within a specified time. The goal of the proposed model is to comprehensively optimize vehicle usage costs, transportation costs, time penalty costs, and carbon emissions costs in ULDN. The customer location, customer demand, and time window are known, and the urban traffic congestion period and traffic congestion status can be obtained from the transportation department.

The proposed model and algorithm will provide valuable guidance for logistics companies and transportation departments in urban areas to optimize their logistics network and reduce transportation costs while considering the impact of traffic congestion and low-carbon emissions. By reducing carbon emissions and optimizing vehicle routing, this research can help mitigate the negative impact of logistics activities on the environment and promote sustainable development.

3.2 Assumptions

In the proposed model, the following assumptions are made:

(1) Only one distribution center with sufficient supply is considered.
(2) The delivery vehicles are of the same type and depart from the logistics center at different times as needed, returning to the same logistics center afterward.
(3) Customer demand is less than the vehicle capacity, and there is a service time window requirement.
(4) During periods of traffic congestion, vehicles travel at a congested speed, while during non-congested periods, vehicles travel at normal speeds.
(5) The maximum load capacity of each vehicle is fixed, and each customer is served by only one vehicle.
(6) Vehicles generate carbon emissions during driving time and do not generate carbon emissions during the rest of the time.

By considering these assumptions, the proposed model provides a practical and realistic approach for logistics companies and transportation departments to optimize their logistics network while reducing carbon emissions and transportation costs. The proposed model and algorithm can be used to guide logistics companies in making informed decisions on vehicle routing and scheduling, ultimately improving the efficiency and sustainability of urban logistics distribution networks.

3.3 Notations

I	Set of customers
I'	Set of all nodes in the urban logistics distribution network
J	Set of routes
K	Set of vehicles
N	Set of road section
f_k	Fixed departure cost of vehicles k
t_{ijkn}	The time consumed by the vehicle k traveling on road segment n in road (i, j)
O	Unit time cost of vehicle usage
D	Unit human resource cost of vehicles
Q	Maximum vehicle load capacity
q_i	The demand for customer i;
ct_i	Unloading service time at customer i
T_{ik}	Waiting time for vehicle k to arrive at customer i in advance
v_{ijkn}	The traveling speed of the vehicle k in the section n of the road (i, j)
t_{ijkn}	The time consumed by the vehicle k traveling on road segment n in road (i, j)
β_{ijkn}	Carbon emission rate of vehicle k in section n of road (i, j) (kg/km)
d_{ijkn}	The distance travelled by vehicle k in section n of road (i, j)
δ	Unit carbon emission cost (yuan/kg)
g	Unit fuel consumption cost (yuan/L);
θ_{ijkn}	The fuel consumption rate of the vehicle k in the section n of the road (i, j) (L/km)
RT_{ik}	The time when the vehicle k arrives at the customer i
LT_{ik}	The time when the vehicle k leaves the customer i
$[E_j, L_j]$	The service time window for customer i
α_{de}	The penalty factor when the vehicle arrives early
α_{dl}	The penalty factor when the vehicle arrives late
λ_{ij}	Traffic congestion coefficient

$$x_{ijk} = \begin{cases} 1 & \text{If vehicle } k \text{ travel in the path } (i,j) \\ 0 & \text{otherwise} \end{cases} \quad i \in I, j \in I, k \in K$$

$$Y_{jk} = \begin{cases} 1 & \text{If vehicle } k \text{ serves consumer } j \\ 0 & \text{otherwise} \end{cases} \quad j \in I, k \in K$$

$$U_{ijkn} = \begin{cases} 1 & \text{If vehicle } k \text{ travel in the path } n \\ 0 & \text{otherwise} \end{cases} \quad \mathrm{i} \in I, \mathrm{j} \in J, \mathrm{k} \in K, n \in N$$

$$r_k = \begin{cases} 1 & \text{If vehicle } k \text{ is used} \\ 0 & \text{otherwise} \end{cases} \quad k \in K$$

3.4 Mathematical model

With the rapid increase in urban cars, traffic congestion has become a common phenomenon in urban areas. The impact of traffic congestion on logistics delivery efficiency and quality makes it necessary to consider the space-time effect in ULDN. The shortest path between two customers should not be based on the shortest spatial distance but rather on the shortest time, which varies due to different road congestion conditions and vehicle speeds during different periods of time. To quantify the degree of road congestion, the paper introduces a traffic congestion coefficient λ_{ij}. The speed on the road during congestion $v_c = v_f/\lambda_{ij}$, where v_f is the vehicle speed when the road is clear. When the vehicle travels on a sub-road section with a sufficiently short distance, the speed can be considered constant based on the actual situation and driving rules.

In the proposed urban logistics network optimization model, the carbon emission cost, vehicle usage cost, transportation cost, and time penalty cost are considered. They are calculated as follows:

(1) Carbon emission cost

Carbon emissions are mainly generated during vehicle transportation, and the carbon emission coefficient is used to calculate the carbon emissions during transportation. The carbon emission coefficient represents the unit carbon emissions of the logistics distribution, which quantifies the total carbon dioxide content in the logistics distribution. The carbon emission cost C_1 is calculated using Eq. 1.

$$C_1 = \sum_{i \in I} \sum_{j \in I} \sum_{k \in K} \sum_{n \in N} \beta_{ijkn} U_{ijkn} \, v_{ijkn} t_{ijkn} \tag{1}$$

(2) Vehicle usage cost

Vehicle usage costs mainly include vehicle departure costs, vehicle rental costs, and labour costs. The vehicle rental cost and labour cost are the product of the total travel time and unit cost. The total travel time is the sum of road travel time, customer service unloading time, and waiting time at the customer point. Therefore, the vehicle management usage cost C_2 is calculated using Eq. 2.

$$C_2 = \sum_{k \in K} r_k \, f_k + \sum_{i \in I} \sum_{j \in I} \sum_{k \in K} \sum_{n \in N} U_{ijkn} \, t_{ijkn} (O + D) + (\sum_{j \in I} \sum_{k \in K} y_{jk} ct_j + \sum_{j \in I} \sum_{k \in K} y_{jk} T_{jk})(O + D) \tag{2}$$

(3) Transportation cost

Transportation cost refers to the fuel consumption cost generated during vehicle transportation. The transportation cost C_3 is calculated using Eq. 3.

$$C_3 = \sum_{i \in I} \sum_{j \in I} \sum_{k \in K} \sum_{n \in N} g U_{ijkn} \, v_{ijkn} t_{ijkn} \theta_{ijkn} \tag{3}$$

(4) Time penalty cost

In the process of urban logistics distribution, scheduling errors, and low delivery efficiency may cause distribution vehicles to miss the specified delivery time. Such delays may negatively impact customers, such as supermarkets and shopping malls, which have their own business hours. Delayed delivery times may increase the cost of the enterprise due to decreased customer satisfaction, and penalties should be imposed accordingly. The penalty cost in the vehicle distribution is calculated using Eq. 4.

$$C_4 = \alpha_{de} \sum_{i \in I} \sum_{k \in K} (E_{ik} - RT_{ik}, 0) + \alpha_{dl} \sum_{i \in I} \sum_{k \in K} (RT_{ik} - L_{ik}, 0) \tag{4}$$

By considering these costs, the proposed model and algorithm can provide valuable guidance for logistics companies and transportation departments in urban areas to optimize their logistics network while reducing transportation costs and carbon emissions. The $E_{ik} - RT_{ik}$ is the waiting time for vehicle k to arrive at customer i in advance, and $RT_{ik} - L_{ik}$ is the waiting time for customer i due to vehicle lateness.

The objective function of the proposed VRP model in ULDN is constructed as follows:

$$min \, Z_1 = \sum_{i \in I} \sum_{j \in I} \sum_{k \in K} \sum_{n \in N} \beta_{ijkn} U_{ijkn} \, v_{ijkn} t_{ijkn} \tag{5}$$

$$min \, Z_2 = \sum_{k \in K} r_k \, f_k + \sum_{i \in I} \sum_{j \in I} \sum_{k \in K} \sum_{n \in N} U_{ijkn} \, t_{ijkn} (O + D) + (\sum_{j \in I} \sum_{k \in K} y_{jk} ct_j + \sum_{j \in I} \sum_{k \in K} y_{jk} T_{jk})(O + D) \tag{6}$$

$$min\, Z_3 = \sum_{i \in I} \sum_{j \in I} \sum_{k \in K} \sum_{n \in N} gU_{ijkn}\, v_{ijkn} t_{ijkn} \theta_{ijkn} \tag{7}$$

$$min\, Z_4 = \alpha_{de} \sum_{i \in I} \sum_{k \in K} (E_{ik} - RT_{ik}, 0) + \alpha_{dl} \sum_{i \in I} \sum_{k \in K} (RT_{ik} - L_{ik}, 0) \tag{8}$$

Subject to

$$\sum_{k \in K} x_{ijk} = 1\,, \forall (i,j) \in J \tag{9}$$

$$\sum_{k \in K} y_{jk} = 1\,, \forall j \in I \tag{10}$$

$$x_{ijk} \geq U_{ijkn}, \forall (i,j) \in J, k \in K, h \in H \tag{11}$$

$$x_{ijk} \leq \textstyle\sum_{n \in N} U_{ijk}\,, \forall (i,j) \in J, k \in K \tag{12}$$

$$\sum_{k \in K} \sum_{n \in N} d_{ijkn} U_{ijkn} = x_{ijk} d_{ijkn}, \forall (i,j) \in J, k \in K, n \in N \tag{13}$$

$$\sum_{j \in I'} x_{0jk} \leq 1\,, \forall k \in K \tag{14}$$

$$d_{ijkn} \leq d_{ij} U_{ijkn}, \forall (i,j) \in J, k \in K, n \in N \tag{15}$$

$$\sum_{j \in J} q_j\, y_{jk} \leq Q, \forall k \in K \tag{16}$$

$$x_{ijk} \in \{0,1\} \tag{17}$$

$$y_{jk} \in \{0,1\} \tag{18}$$

$$U_{ijkn} \in \{0,1\} \tag{19}$$

$$r_k \in \{0,1\} \tag{20}$$

Eq. 9 indicates that only one vehicle is allowed to drive on the selected road. Eq. 10 indicates that each customer can only be served by one vehicle, and all customers must be served. Eqs. 11 and 12 represent the limiting relationship between variables x_{ijk} and U_{ijkn}. Eq. 13 indicates that the vehicle should travel the entire road as long as the road is selected. Eq. 14 indicates that each vehicle is only used once. Eq. 15 represents the restriction relationship between d_{ijkn} and d_{ij}. Eq.16 represents vehicle capacity constraints. Eqs. 17-20 represent variable value constraints.

By considering these constraints and the objective function, the proposed model and algorithm can optimize vehicle usage costs, transportation costs, time penalty costs, and carbon emissions costs in ULDN while considering traffic congestion. This approach can help logistics companies and transportation departments in urban areas to optimize their logistics network and reduce transportation costs and carbon emissions, ultimately promoting sustainable development.

4. Improved Discrete Particle Swarm Optimization

The Particle Swarm Optimization (PSO) is a global optimization algorithm based on swarm intelligence, which was proposed by American scholars Kennedy and Eberhart [41]. The PSO algorithm simulates the social behaviour of animal groups, such as flocks of birds and fish, by following three typical rules: 1) Fly away from the nearest individual to avoid collisions; 2) Fly towards a predetermined goal; 3) Fly to the center of the group. For example, a flock of birds usually determines its flight direction and speed based on its own flight experience, which leads to consistent flock behavior. However, when one bird in the group changes direction and flies to a new habitat, other birds will also be affected and fly to the new habitat, causing the remaining birds to imitate this behaviour until they all fall into the new habitat.

In the PSO algorithm, each possible solution in a population is represented as a particle without volume or mass. All such particles fly at a certain speed in the search space, and their speed is derived from past flight experience. The PSO algorithm enables the entire population to develop towards global optimization through information sharing among particles. It has the ability to search multiple points and can obtain multiple Pareto optimal solutions through one operation. Therefore, the advantages of the PSO algorithm are suitable for solving multi-objective optimization problems in urban logistics networks.

To further improve the PSO algorithm, the paper proposes an improved discrete particle swarm optimization algorithm (DPSO) to solve the VRP model in ULDN. The DPSO algorithm uses multiple populations to process multiple targets and develops a variable neighbourhood search strategy to improve the search ability of particles. The DPSO conducts a randomized deep search to improve the "premature convergence" problem of the PSO algorithm, which improves the quality of understanding.

(1) Coding of the DPSO

To implement the DPSO algorithm for solving the VRP model in ULDN, the solution space of VRP in ULDN is represented by a directed complete graph, denoted as $G = (V, E)$, where each potential solution is a generated subgraph of G. The search space of the entire particle swarm is the arc set E in the complete graph G. The position of each particle is represented by a set consisting of arcs, forming a subset A. The search space of the particle swarm is the edge set of the directed complete graph of urban logistics distribution customer nodes. The position of a particle is a subset of the edge set of a complete graph, and the edges in this subset are connected end-to-end to form a directed Hamilton loop, serving as the distribution path for logistics vehicles.

The speed of a particle is a collection of all nodes, and edges in the speed collection may be selected to build a new location for the particle. Each element in the individual is converted to a number in the floating point interval [0,1]. The velocities of all particles are calculated, and then the element is converted to an integer based on the relative position index.

(2) Particle position update

The DPSO algorithm for solving the VRP model in ULDN uses n candidate solutions to find the optimal solution in the search space. The position vector corresponding to the particle is represented by $X_i = [x_i^0, x_i^1, \dots, x_i^n]$, where each dimension of X is represented by $x_i^d = [(m,d),(d,k)], m, d \in \{0,1,\dots,d-1,d+1,n\}, m \neq k$. Each individual in the population represents a feasible solution, and x_i^d is composed of two arcs connected by customer d. n is the total dimension (total number of customers), d represents the current dimension index, m is the predecessor node of customer t (the customer served before customer t), and k is the successor node of customer t (the customer served after customer t). Eq. 21 is used to update the position of particles.

$$v_{i_d}(t+1) = v_{id}(t) + c_1 \times r_1 \times (pb_{id}(t) - x_{id}(t)) + c_2 \times r_2 \times (gb_d(t) - x_{id}(t)) \tag{21}$$

The velocity of particle i in the d-th dimension at the t-th iteration is represented as $v_{id}(t) \in R$, and $PB_i(t) = (pb_{i1}(t), pb_{i2}(t), \dots, pb_{id}(t), \dots, pb_{iD}(t))$ is the position of the individual historical extreme value of particle i up to the t iteration. $GB(t) = (gb_1(t), gb_2(t), \dots, gb_d(t), \dots, gb_D(t))$ is the best position experienced by all particles in the population up to the t iteration. Each particle updates its own velocity and location based on individual historical extremum and global optimal value. The t represents the t-th search, $V_i(t)$ represents the speed of the i-th particle, $X_i(t)$ is the current position of the i-th particle, r_1 and r_2 are random numbers between (0,1), and the constants c_1 and c_2 are learning factors, usually taking the same value between 0 and 2.

(3) Particle Speed Update

In the DPSO algorithm for solving the VRP model in ULDN, when the optimization value of particle i changes very little, the speed of the particle is updated according to Eq. 22, where α_i defines the historical optimal value of particle i. For each dimension of each particle in the D-dimensional space, the corresponding dimension of the historical optimal value of one particle is selected from all particles according to a certain probability to learn. Thereby, a learning particle is constructed randomly for each particle i. Each dimension of each particle in the population learns from the optimal solution set with a probability p.

The particle speeds are updated by Eqs. 22 and 23, where *Gbest* is the optimal solution set, and G is the number of candidate solutions in the optimal solution set, which is equal to the number of population sizes.

$$V_i^d = w \times V_i^d + c \times rand_i^d \times \left(Gbest_{f_i(d)}^d - X_i^d\right) \tag{22}$$

$$\rho C_p \left(\frac{\partial T}{\partial t} + u \cdot \nabla T\right) = \nabla(k \nabla T) + \eta \dot{\gamma}^2 \tag{23}$$

(4) Variable neighbourhood search

During the operation of PSO, particle swarm optimization may quickly approach the current optimal position of the population, which can lead to weak global search ability and the "premature convergence" phenomenon. To address this issue, the DPSO algorithm utilizes variable neighbourhood search local search operators, which can expand the local search space and improve the quality of individual search, thereby improving the group optimization ability.

In the DPSO algorithm for solving the VRP model in ULDN, the vehicle route that passes through the least number of customers is selected to determine the individual and global extrema. Then, under certain hypothetical conditions, the customer closest to the current route is selected to be inserted, and it is determined whether at least that customer exists in another vehicle route. If it exists, the location where the total logistics cost of the new route is the smallest is selected, and if it does not exist, it will not be inserted. The optimal solution set is updated after completing the above operation.

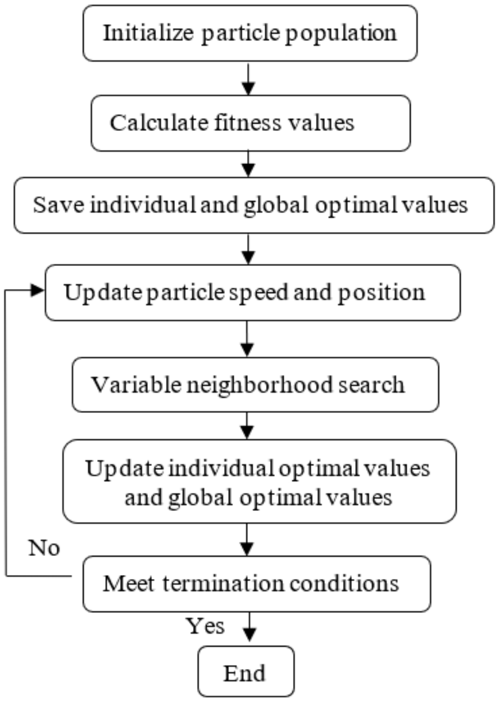

Fig. 1 Algorithm steps of DPSO

The specific steps of variable domain search are as follows:

For $L1(s)$:
Step 1: Select a path R randomly.
Step 2: Select two nodes $N1$ and $N2$ in path R randomly.
Step 3: Exchange $N1$ and $N2$.

For $L2(s)$：
Step 1: Select two paths $R1$ and $R2$ randomly.
Step 2: Select a node $N1$ randomly in path $R1$, and select a node $N2$ randomly in path $R2$.
Step 3: Exchange $N1$ and $N2$.

For $L3(s)$：
Step 1: Select the path R with the lowest bearing capacity.
Step 2: Insert the customers in the distribution path R into other distribution paths.

(5) Algorithm Steps

The DPSO steps is as follows:
Step 1: Initialize the particle population and initialize each particle randomly.
Step 2: Update the speed and position of each particle.
Step 3: Local search on the optimal solution set.
Step 4: Update the optimal solution set. If the stop condition is not satisfied, return to Step 2 to continue optimizing the population.
Step 5: Terminate the entire algorithm and obtain the optimal solution set. The specific steps are shown in Fig. 1.

5. Simulation

Based on the urban logistics distribution data of a logistics enterprise in Shanghai, the DPSO algorithm is applied to optimize the logistics network. The logistics enterprise distributes products to various consumers in Shanghai, and has one logistics distribution center that needs to meet the distribution needs of 50 stores and supermarkets (customers). The number 0 refers to the logistics distribution center, and the numbers 1-50 refer to the consumers.

The initial time is set as 6:00 a.m., and this time is set as 0 o'clock in the model. According to urban traffic laws, the time periods between 7:00 to 9:00 and 17:00 to 19:00 are considered as traffic congestion periods, and the rest of the time periods are considered as normal driving periods. Under a time-varying network, the normal driving speed v_f is 60 km/h, and the speed v_c during congestion is 30 km/h. The vehicle has an unloaded weight of 5000 kg and a capacity of 2t.

The values of other parameters are shown in Table 1. The parameters of the DPSO algorithm are set as follows: the population size is 50, the number of iterations is 100, $w = 0.7$, $c_1 = c_2 = 1.5$, $r_1 = r_2 = 0.5$.

The simulation experiment using the DPSO algorithm to optimize the logistics network of a logistics enterprise in Shanghai took 180.2 s to execute. Seven vehicles were used for distribution, and the total distribution cost was 5240 yuan. The vehicle usage costs (vehicle startup and rental fees) were 2305 yuan, the transportation cost was 2638 yuan, the carbon emission cost was 103 yuan, and the time penalty cost was 194 yuan. The optimization results are shown in Table 2.

The optimization results indicate that the DPSO algorithm can obtain optimal routes in a relatively short time. Vehicles 3 and 5 completely avoided the congestion period, while vehicles 1, 4, and 6 had two sections in the morning and evening peak congestion periods. Vehicle 2 had two sections in the morning and evening peak congestion period, and vehicle 7 had three sections in the morning and evening peak congestion period. This indicates that the proposed DPSO algorithm can reasonably avoid traffic congestion periods and improve vehicle delivery efficiency.

Table 1 Parameters

Parameters	Value
f_k	130yuan/vehicle
O	6yuan/h
D	10yuan/h
δ	0.5yuan/kg
g	6yuan/L
α_{de}	10yuan/h
α_{dl}	10yuan/h
v_f	60km/h
v_c	30 km/h

Table 2 Optimization results of urban logistics distribution network

Route	Distribution route	Number of routes during congestion periods	Carbon emission cost	Vehicle usage costs	Transport-ation cost	Time penalty cost	Total cost
1	0-4-5-10-12-15-20-21-0	1	11	286	325	26	648
2	0-1-6-7-25-41-8-16-44-0	2	15	355	410	45	825
3	0-32-45-28-0	0	8	167	203	0	378
4	0-14-2-17-19-49-38-26-0	1	14	290	348	23	675
5	0-42-31-23-3-9-18-43-0	0	12	348	322	0	682
6	0-22-11-13-34-47-27-50-36-0	1	19	365	402	21	807
7	0-29-46-24-33-35-30-39-40-48-37-0	3	24	494	628	79	1225

Based on the comprehensive distribution route optimization results, it can be found that due to the constraints of urban congestion and customer service time windows, there are significant differences in the distribution routes. The maximum number of customers served by vehicle 7 is 10, while the number of customers served by vehicle 3 is the lowest, with only 3. This is due to the different time windows at each customer, indicating that logistics enterprises should consider time dependence when planning their routes. Logistics enterprises should plan their routes scientifically based on the actual conditions such as road network conditions and customer time windows.

In addition, the impact of traffic congestion on the optimization results of VRP in ULDN is illustrated in the paper. The traffic congestion coefficient λ_{ij} is set to 1.5, 2.0, 2.5, and 3.0, with corresponding congestion speeds of 40 km/h, 30 km/h, 24 km/h, and 20 km/h, while the normal driving speed v_f remains unchanged at 60 km/h. The optimization results are shown in Table 3.

Table 3 Optimization results for different traffic congestion coefficient

Traffic congestion coefficient	Number of delivery vehicles	Carbon emission cost	Vehicle usage costs	Transportation cost	Time penalty cost	Total cost
1.5	7	89	2260	2554	181	5084
2.0	7	106	2302	2644	199	5251
2.5	8	134	2377	2880	221	5612
3.0	9	165	2456	3012	247	5880

From the perspective of the optimization process of the DPSO algorithm, the optimal evolution iterations corresponding to different traffic congestion coefficients fluctuate slightly between 30 and 45 generations after 100 iterations. Although the change in vehicle usage costs is not significant, the optimal values of transportation costs, carbon emissions costs, and time penalty costs increase as the traffic congestion coefficient increases, leading to an increase in total costs. As the congestion coefficient increases, fuel consumption and carbon emissions increase, indicating that congestion conditions can affect the greenness of logistics delivery routes. The cost of time penalty increases, which indicates that traffic congestion can affect vehicle speed and affect the service time.

Furthermore, the effectiveness of the DPSO algorithm is verified by comparing the optimization results of DPSO with the basic PSO algorithm. The convergence of the two algorithms within 100 iterations is obtained under the same parameter settings. The parameters of the algorithm are: the population size is 50, the number of iterations is 100, $w = 0.7$, $c_1 = c_2 = 1.5$, $r_1 = r_2 = 0.5$. The optimization results of DPSO and PSO are shown in Figure 2.

The optimization results of the DPSO algorithm show that the minimum value of the total cost maintains an overall downward trend with the increase of genetic iterations. Meanwhile, the convergence of the DPSO algorithm is significantly better than that of the PSO algorithm. The DPSO algorithm basically reaches the optimal solution around the 35th generation, while the PSO algorithm converges to the optimal solution in the 80th generation, and its overall optimization cost is greater than that of the DPSO algorithm. This indicates the effectiveness of the DPSO algorithm in optimizing the logistics network in ULDN and improving the efficiency of vehicle delivery.

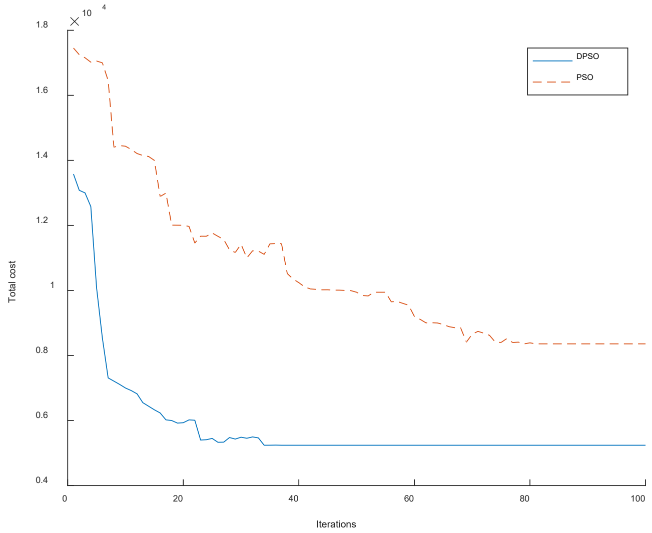

Fig. 2 Comparison of the optimal total cost

6. Conclusions

In this paper, we proposed a model of vehicle routing problem in urban logistics distribution under traffic congestion, taking into account vehicle management costs, transportation costs, carbon emissions costs, and penalty costs comprehensively. To solve this complex multi-objective optimization problem, we developed an improved DPSO algorithm based on the PSO, which uses multiple populations to process multiple targets, and incorporates a variable neighbourhood search strategy to improve the search ability of particles. The randomized deep search was also conducted to improve the "premature convergence" problem of PSO, which improves the quality of optimization results.

The simulation results showed that our proposed model can obtain the lowest cost and optimal delivery route, effectively avoiding traffic congestion, reducing carbon emissions costs and penalty costs, and improving customer satisfaction. Comparative analysis of optimization results between the DPSO and the PSO showed that the proposed DPSO algorithm has better convergence and effectiveness in VRP of urban logistics distribution.

Our proposed model and algorithm provide effective solutions and references for solving practical logistics distribution network optimization problems in urban areas with complex traffic conditions. By optimizing delivery routes, logistics enterprises can reduce transportation costs, carbon emissions, and penalties, while improving customer satisfaction and promoting sustainable development in urban logistics. In summary, our study contributes to the field of urban logistics distribution and provides a valuable reference for future research in this area. The types of vehicles and the dynamic changes in customer demand are not considered in the study. Future research could introduce different types of delivery vehicles and dynamic changes in customer demand in the delivery paths optimization.

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