Distribution Path Optimization for Intelligent Logistics Vehicles of Urban Rail Transportation Using VRP Optimization Model

Kaijun Leng and Shanghong Li

***Abstract*— Path optimization of logistics distribution vehicles is researched to improve the efficiency of intelligent logistics systems. The logistics distribution system based on urban rail transportation is analyzed. A mathematical model is constructed for the Vehicle Routing Problem (VRP) of multiple distribution centers. A novel Concentration-Immune Algorithm Particle Swarm Optimization (C-IAPSO) is proposed based on the respective advantages of C-IA and PSO in vehicle path optimization combining the concept of antibody concentration. C-IAPSO first calculates the concentration selection probability of particles in the swarm and updates the immune memory bank as per the optimal particle retention strategy to ensure the diversity of the antibody swarm. To assess the performance of C-IAPSO, seven standard test functions are selected for comparison experiments; results prove that it can provide the fastest convergence rate. On unimodal functions Sphere and Quadric, the accuracy of C-IAPSO gets improved significantly. The specific conditions of the distribution center and the demand spots are analyzed; the vehicle travels 508.40 km in total under the optimal distribution path calculated by C-IAPSO, which is a notable decrease compared with the 600.40 km of Adaptive PSO (APSO). To sum up, applying C-IAPSO to vehicle path optimization of intelligent logistics systems can improve transportation efficiency and reduce transportation costs.**

***Index Terms*— Vehicle routing problem, urban rail transportation, intelligent logistics system, distribution vehicle, immune algorithm particle swarm optimization (IAPSO).**

I. Introduction

LOGISTICS has become the core infrastructure for urban development with the gradual development of smart cities worldwide [1]–[3]. Urbanization advancement leads to distinct divisions in the nature of regional land use. Besides the influences of e-commerce on traditional shopping models, logistics distribution originally dominated by urban rail transportation has continuously increased transportation network loads. The core of urban development is resource allocation. Resource sharing is a vital pattern to increase social resource allocation efficiency, while the logistics industry naturally has conditions for resource co-allocation [4]. Urban rail transportation has a vast coverage, consumes a small amount of energy, and runs quickly. Fully utilizing these advantages can effectively ease the pressure on urban logistics distribution, circulate materials between cities, and reasonably allocate urban public resources.

Distribution is a vital link to modern logistics, playing an increasingly significant role in the entire logistics system with its globalization and informationization [5], [6]. Distribution connects production and consumption. It refers to the logistics activities of timely distributing and delivering goods in logistics distribution centers to consignees according to order requirements. Research on "distribution" discusses where to establish distribution centers and explores the Traveling Salesman Problem (TSP) and Vehicle Routing Problem (VRP). A reasonable distribution is critical to distribution decision systems, and reasonable distribution routes are crucial to a reasonable distribution [7], [8]. A distribution path optimization model can understand the road conditions at all times and the generation of new orders, considering dynamic information changes. Information can be better shared with the support and cooperation of distribution decision centers and traffic information centers. VRP is one of the most basic problems in network optimization, which has been broadly applied in logistics distribution [9]–[11]. The logistics distribution link in modern logistics systems requires taking the shortest path to deliver the goods in the warehouse to the destination. Optimizing the transportation path of distribution vehicles is of great significance for improving transportation efficiency and reducing logistics costs.

It is intelligent distribution path selection that can reduce the cost of logistics distribution and promote the overall development of the logistics industry. A routing mathematical model for multiple distribution centers is designed based on traditional logistics distribution systems, and an intelligent logistics distribution system of urban rail transportation is constructed. Applications of Immune Algorithm (IA) and Particle Swarm Optimization (PSO) in solving VRP are analyzed. Afterward, an IAPSO model considering antibody concentration (written as C-IAPSO) is proposed. Hence, the swarm diversity can be guaranteed, and logistics intelligent distribution paths can be optimized. The proposed algorithm is applied to solve the actual distribution vehicle routing in simulation experiments to verify its feasibility. The research explores the method of improving and perfecting PSO, to expand the application field of the algorithm.

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II. Current Research Works on Vehicle Routing in Logistics Distribution

A. Logistics Distribution Service of Urban Rail Transportation

Urban rail transportation is an emerging urban freight transportation method in many countries. Passenger trains and freight trains share the same railway in this system to provide logistics distribution services. Ozturk and Patrick (2018) proposed a decision support framework for urban rail freight transportation problems. Goods could be transported from the departure station to the arrival station, and the approximate and dynamic programming algorithms for the two-station situation were given, correspondingly [12]. Jiang *et al.* (2019) proposed a Q-learning-based coordination scheme for traffic congestion of logistics distribution in urban rail transportation [13]. This scheme could ease the pressure on traffic demand and solve the train operation on urban rail transportation lines. Qi and Hu (2020) established an emergency cold chain logistics scheduling mathematical model, including vehicle loss, refrigeration consumption, and goods damage. They utilized heuristic algorithms to solve the emergency cold chain logistics scheduling model [14]. This model could adaptively adjust the pheromone update strategy and provide strong applicability and potential advantages in emergency rescues.

B. Vehicle Path Optimization

Under fierce market competition, distributing and delivering goods within time frames expected by customers become increasingly essential. Hence, vehicle path optimization has attracted much attention. Guo *et al.* (2017) considered vehicle loads and travel distances. They constructed a dynamic multi-objective vehicle path optimization model with a hard time window [15]. A multi-objective PSO was applied to find the best robust virtual path for all vehicles in the first stage. All dynamic vehicles were removed from the robust virtual path to form a static customer vehicle path in the second stage. Qin *et al.* (2019) put forward a comprehensive optimization model of vehicle routing that took customer satisfaction and cost minimization as the objective functions. Then, they tested the model with the nomogenesis Genetic Algorithm (GA) [16]. A slight increase in the total cost can greatly improve the average customer satisfaction, resulting in a cost-effective solution. Zhang *et al.* (2019) believed that distribution plans should minimize the total transportation cost while balancing the profits of all transportation companies [17]. They developed a multi-objective Local Search Algorithm (LSA) to solve this problem and maximized the minimum unit profit of each transportation company to balance the profit.

Vehicle path optimization in logistics distribution systems supported by urban rail transportation has received widespread attention. At present, most research focuses on single-objective path optimization. However, complex systems, such as logistics distribution, contain multiple distribution centers and destinations, requiring investigating the VRP mathematical model in-depth. The algorithm will be improved in the present work to solve the vehicle path optimization in logistics distribution based on previous works.

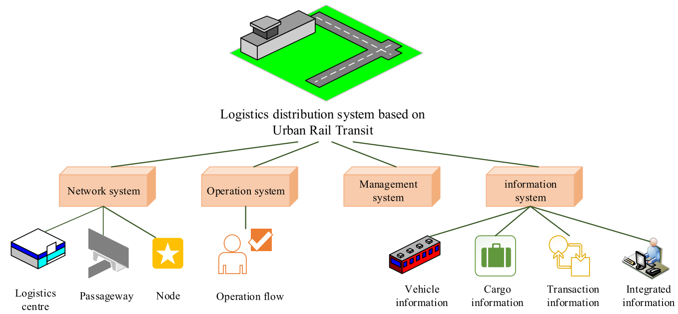

Fig. 1. Composition of logistics distribution system based on urban rail transportation.

III. Path Optimization Model Based on Concentration-Immune Algorithm Particle Swarm Optimization

A. Logistics Distribution System Based on Urban Rail Transportation

The urban logistics distribution system is an organic whole comprising multiple sub-systems that contain and cooperate with each other to provide logistics distribution services for users in the city. Urban distribution is both the middle-end and the terminal of logistics activities. Its radiation range is as large as urban interoperability and as small as communities, villages, and towns. It is a concentrated area of urban circulation contradictions. The urban distribution system comprises the urban distribution network system, the urban distribution operation system, and the urban distribution information system. The urban common distribution model is based on urban distribution business socialization and third-party operations; it distributes and delivers materials in the same demand area to the vehicles of unified service centers for unified transportation and distribution based on spatial integration and information integrated sharing.

An urban logistics distribution system includes four links: input, output, interference processing, and feedback [18], [19]. As the informatization degree gets higher, the spread of logistics information becomes faster. Using urban rail transportation for logistics distribution can improve the distribution efficiency and quality and reuse the residual value of urban rail transportation [20]. Sub-systems of urban rail transportation are analyzed; afterward, a logistics distribution system is established based on urban rail transportation. Its structure is illustrated in Figure 1.

Urban logistics distribution network system refers to the process that goods are sent from suppliers through logistics nodes such as logistics center and distribution center, and transported to customers or demand points through transportation channels, mainly composed of nodes and channels. The urban logistics distribution operation system covers many contents, such as the distribution process of goods, the configuration of staff in the system, and enterprise publicity.

Urban logistics distribution management system usually consists of two parts: government management and enterprise internal management. The government introduces a series of policies to realize the guidance and supervision of logistics service enterprises. Then, the enterprise adjusts and manages the data, staff and software and hardware according to its own development trend to promote the healthy development of enterprises. The function of urban logistics distribution information system is to collect, collate, transmit, save and transport information in the system, thereby coordinating the organization of goods and vehicles and improve the efficiency of logistics distribution.

Logistics distribution networks with urban rail transportation can update logistics distribution channels besides logistics distribution centers that traditional logistics distribution systems have, including ground channels and rail channels. In traditional distribution channels, goods are sent from logistics centers and distributed to customers via ground road networks. In updated logistics distribution channels, if there is a functional node near the customer, goods will be sent to the functional node via the urban rail transportation networks and then stored. Afterward, the customer can pick up the goods. Usually, the coordination between rail transportation and ground road networks is required to implement the whole logistics distribution process. Rail channels serve urban passenger transportation systems, including subway, light rail, and magnetically levitated trains, and urban fast rail systems, suitable for medium and long-distance distribution [21]. Ground channel uses road transportation as the carrier, and the distribution is more flexible.

Generally, while applying urban rail transportation to logistics distribution services, first, it is necessary to fully meet the needs of customers and ensure that the transportation capacity can be fully utilized [22]. On this basis, rail transportation should be chosen as the primary logistics distribution channel to reduce urban congestion and transportation costs, thereby improving transportation efficiency. In the future, urban distribution companies will occupy the chain-master position and become a vital link to their core competitiveness. From business stripping and socialization to integration, urban distribution companies are likely to become the chain-masters of the regional commerce and logistics chains.

B. Routing Mathematical Model of Multiple Distribution Centers in VRP

Routing of multiple distribution centers is extended from VRP. Actual logistics distribution problems usually contain multiple distribution centers and destinations intertwined mutually. The corresponding distribution center is selected based on customer needs, and the most reasonable route is planned [23]. The structure of multiple distribution centers VRP is illustrated in Figure 2. Suppose there are two distribution centers, A and B, and customer service points are scattered. In that case, two distribution centers arrange three vehicles to distribute under their constraints, and finally, make the total path for the two distribution centers to complete all the distributions the shortest. While routing for multiple

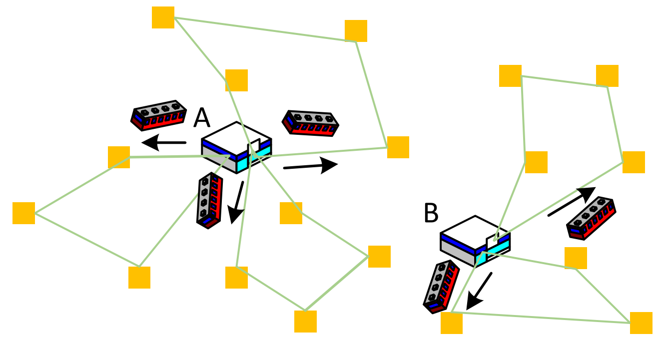

Fig. 2. Composition of logistics distribution system based on urban rail transportation.

distribution centers, multiple distribution points can be converted into a single distribution point using the decomposition method and the overall method. The former calculates the distance between each customer service point and the distribution center based on the nearest distribution principle. It converts the large-scale problem into multiple simple VRP solutions [24]. The overall method considers each distribution center as a whole, establishes a virtual distribution center, evaluates each actual distribution center, and optimizes it as a whole to obtain the global optimal solution.

Suppose that a logistics company has M distribution centers to distribute all goods, corresponding to N customer service points, the m-th distribution center can send C_m vehicles to distribute goods to N_m demand spots, and the goods capacity of each vehicle is Q_{mc}. In that case, some demand spots should exist on each path, and the i-th demand spot served by the m-th distribution center is required to have a good receiving capacity of V_{mi}, satisfying $V_{mi} < Q_{mc}$. While meeting the distribution vehicle's approved goods capacity, each vehicle can only choose one route at a time and provide distribution services for multiple demand spots on the route. Under the constraints, a mathematical model is constructed for logistics distribution path optimization of multiple distribution centers. The objective function of the optimization problem can be expressed as equation (1), where the total distance traveled by all vehicles to complete the distribution tasks is the shortest.

$$\min Z = \sum_{m=1}^{M} \left\{ \sum_{k=1}^{C_m} \left[\sum_{i=1}^{n_{mc}} \left(d_{r_{mc(i-1)} r_{mci}} + d_{r_{mcn_{mc}} r_{mc0}} \varphi\left(n_{mc}\right) \right) \right] \right\} \tag{1}$$

$$\sum_{i=1}^{n_{mi}} V_{mr_{mci}} \leq Q_{mc} \tag{2}$$

$$\sum_{i=1}^{n_{mc}} d_{r_{mc(i-1)} r_{mci}} + d_{r_{mcn_{mc}} r_{mc0}} \varphi\left(n_{mc}\right) \leq D_{mc} \tag{3}$$

$$\begin{cases} \displaystyle\sum_{k=1}^{C_m} n_{mc} = N_m \\ \displaystyle\sum_{m=1}^{M} N_m = N \end{cases} \tag{4}$$

$$R_{mc} = \left\{ r_{mci} \left| r_{mci} \in \{1, 2 \ldots n\} \right., i = 1, 2 \ldots n_{mc} \right\} \tag{5}$$

$$R_{mc_1} \cap R_{mc_2} \neq \phi, \quad \forall mc_1 \neq mc_2 \tag{6}$$

In (1) $\sim$ (6), d_{ij} refers to the transportation distance from the demand spot i to the demand spot j, d_{mj} refers to the distance from the distribution center m to the distribution center j, D_{mc} represents the maximum traveling distance of the c-th vehicle in the m-th distribution center for one distribution, $\varphi(n_{mc})$ represents the number of demand spots to which the c-th vehicle in the distribution center m distributes goods, and r_{mci} indicates that the order of demand spot r_{mci} in path R_{mc} is i.

Regarding vehicle routing, the customer will specify the earliest and latest arrival time for the goods, ET_i and LT_i, respectively; the interval $[ET_i, LT_i]$ formed by the two is the time window. Vehicles should complete distribution tasks within the required time window; otherwise, they will be punished. According to customer needs, the time window can be hard or soft. The former requires that the goods distribution time cannot be adjusted. If the goods are not distributed within the time window expected by customers, they will be rejected. The penalty function of the hard time window is:

$$P(t) = \begin{cases} p_0, & t < ET_i,\ t > LT_i \\ 0, & ET_i \le t \le LT_i \end{cases} \tag{7}$$

In (7), p_0 describes the penalty coefficient that the goods delivery time is too early or too late. However, p_0 is not allowed due to the characteristic requirements of the hard time window. Thus, its value will be infinite.

The soft time window puts loose requirements on the goods distribution time than the hard time window. If the actual goods delivery time exceeds the acceptable range, the punishment will not be too large; nevertheless, the more the time window is exceeded, the greater the punishment will be. The penalty function of the soft time window is:

$$P(t) = \begin{cases} p_1(ET_i - t), & t < ET_i \\ 0, & ET_i \le t \le LT_i \\ p_2(t - LT_i), & t > LT_i \end{cases} \tag{8}$$

In (8), p_1 represents the penalty coefficient for the too-early goods distribution time, and p_2 represents the penalty coefficient for the too-late goods distribution time. Values of p_1 and p_2 depend on actual situations. For example, for some goods that require strict temperature control, early distribution may cause additional storage costs for customers; at this time, $p_1 > p_2$.

Penalty functions corresponding to the hard time window and the soft time window are demonstrated in Figure 3.

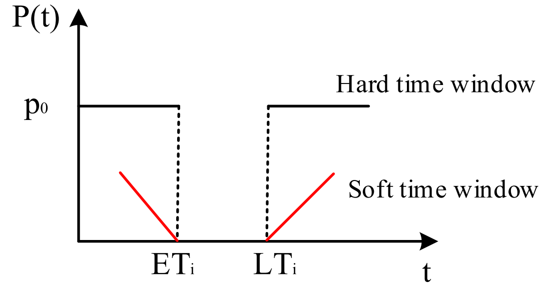

Fig. 3. Penalty functions corresponding to the hard time window and the soft time window.

C. Concentration-Immune Algorithm Particle Swarm Optimization for Vehicle Path Optimization

Routing refers to finding a collision-free path from the start to the target state in an environment with obstacles according to particular criteria. The shortest routing is a classic problem in graph theory research. It aims to find the shortest path between two nodes in a network composed of multiple nodes and paths [25]–[27].

IA applies immune concepts and theories to GA. While retaining the excellent characteristics of the original algorithm, it can selectively use some characteristics of the problem to be solved to suppress the degradation that appears during optimization [28]. IA aims to map the objective function of various optimization problems to be solved with the antigen and find an antibody that can react with the antigen. This antibody is the optimal solution required. The core issue to be addressed is to calculate the affinity and the similarity between antigen and antibody. The higher the affinity, the more likely it is the optimal solution.

The diversity of antibodies in an immune system can be represented by information entropy. If there are N antibodies in an immune system, M genes on each antibody, and S letter representations of each gene: $k_1, k_2 \ldots k_S$; then, the average information entropy of N antibodis is:

$$H(N) = \frac{1}{M}\sum_{j=1}^{M} H_j(N) \tag{9}$$

$$H_j(N) = \sum_{i=1}^{S} -p_{ij}\log p_{ij} \tag{10}$$

In (9) and (10), $H_j(N)$ represents the information entropy of gene j on this antibody, and p_{ij} describes the probability that the allele of the i-th antibody comes from the j-th gene.

Real number encoding is a simple method to encode the antigen and antibody in the immune algorithm. Afterward, the binding strength in the immune algorithm is solved using Hamming distance and Euclidean distance, as shown in equations (11) and (12), respectively:

$$D = \sum_{i=1}^{L}\delta, \quad \begin{cases} \delta = 1, & ab_i \ne ag_i \\ \delta = 0, & other \end{cases} \tag{11}$$

$$D = \sqrt{\sum_{i=1}^{L}(ab_i - ag_i)^2} \tag{12}$$

In (11) and (12), ax_i indicates the affinity between antigen and antibody.

The basic steps of the immune algorithm are: antigen recognition $\rightarrow$ initial antibody generation $\rightarrow$ affinity calculation $\rightarrow$ immune processing (immune selection, cloning, mutation, and suppression) $\rightarrow$ population refresh [29]. An antibody solution set that can enter the next generation is generated through selection and mutation. Usually, the maximum iteration times of the algorithm are set first, and the optimal solution is found after the iterations are finished, as the termination condition for the algorithm to stop the iteration. It is very reasonable to solve logistics routing problems using IA models.

PSO is a global random search algorithm based on swarm intelligence, allowing poor individuals to learn from the better ones. However, the poor individuals are retained to ensure group diversity, showing the group cooperation mechanism [30], [31]. In the D-dimensional target search space, a swarm consists of m particles, where the i-th particle is represented as a D-dimensional vector X_i, and its moving velocity is V_i. When the algorithm is executed, the particle state is updated through equations (13) and (14):

$$v_{id} = wv_{id}+c_1rand_1\left(p_{id}-x_{id}\right)+c_2rand_2\left(p_{gd}-x_{id}\right) \quad (13)$$
$$x_{id} = x_{id} + v_{id} \quad (14)$$

In (13) and (14), x_{id} denotes where the i-th particle in the d-th dimension, v_{id} denotes the velocity of the i-th particle in the d-th dimension, w represents the inertia weight, c_1 and c_2 represent the learning factor, $rand_1$ and $rand_2$ are random numbers on the interval [0, 1], and p_{gd} and p_{id} refer to optimal solution positions currently searched by the i-th particle and the entire swarm.

Based on the linear decreasing strategy of inertia weight, the algorithm can expand the search range in the initial stage and search for possible optimal solutions in the space as much as possible. At the beginning of the search, enhancing the global search ability can traverse the solution space more likely to avoid falling into the local optimal solution. Besides, in the later stage of search, enhancing local search ability can lock the optimal solution more likely. However, in the later stage of the algorithm, a smaller inertia weight can mine a better solution more finely. Particle velocity update in this algorithm can be expressed as:

$$v_{id} = wv_{id}+c_1rand_1\left(p_{id}-x_{id}\right)+c_2rand_2\left(p_{gd}-x_{id}\right) \quad (15)$$
$$w = w_{\max} - \frac{\left(w_{\max} - w_{\min}\right)}{T_{\max}} \times t \quad (16)$$

In (15) and (16), $T_{\max}$ refers to the maximum iteration time, and t denotes the current iteration time.

While updating the particle swarm, particles with higher fitness are often retained and enter the next generation. However, these particles will be concentrated in one area under this update mechanism, affecting the particle diversity and eventually causing the algorithm to fall into a locally optimal solution [32]–[34]. Meanwhile, particles with low fitness but good evolutionary trends will be eliminated. Hence, based on the antibody concentration, an adjustment strategy is proposed to ensure that the particles of different fitness values in the new generation of particle swarms can be maintained within a particular concentration while ensuring population diversity.

The concentration of the i-th particle can be described as:

$$D\left(x_i\right) = \frac{1}{\sum_{j=1}^{N+M}\left|F\left(x_i\right) - F\left(x_j\right)\right|} \quad (17)$$

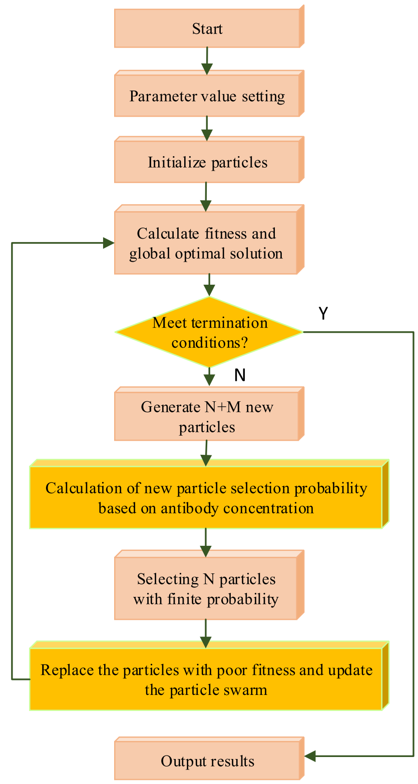

Fig. 4. The flowchart of C-IAPSO.

The selection probability equation based on antibody concentration is expressed as:

$$P\left(x_i\right) = \frac{\frac{1}{D(x_i)}}{\sum_{i=1}^{N+M}\frac{1}{D(x_i)}} = \frac{\sum_{j=1}^{N+M}\left|F\left(x_i\right) - F\left(x_j\right)\right|}{\sum_{i=1}^{N+M}\sum_{j=1}^{N+M}\left|F\left(x_i\right) - F\left(x_j\right)\right|} \quad (18)$$

The probability of antibody i being selected depends on the number of antibodies similar to i; the larger the antibody concentration similar to i, the smaller the probability of i being selected. This adjustment mechanism reduces the fitness and ensures the diversity of antibodies. Moreover, it gives particles with good development trends a chance to be retained for the next generation of evolution. The flowchart of the proposed C-IAPSO is demonstrated in Figure 4.

After generating new particles, C-IAPSO first calculates the concentration selection probability of particles in the swarm and updates the immune memory bank as per the optimal particle retention strategy and the calculated concentration selection probability. The immune memory bank and particle swarm are combined; then, particles are screened to form a new iterative swarm. This method of preserving the optimal particles and then evolving the swarm increases the swarm diversity and can better solve the degradation that occurs after particle swarm update.

D. Applying C-IAPSO to Path Optimization

A logistics company has established three logistics distribution centers L_1, L_2, L_3 in a city, and the coordinates are (18,20), (43,78), and (70,40), respectively. Information

TABLE I
INFORMATION ABOUT 20 DEMAND SPOTS CORRESPONDING TO THE LOGISTICS DISTRIBUTION CENTERS

Numbering of the demand spot	Position coordinates	Amount of demand (t)	Service time (h)
1	(28,65)	1.5	2
2	(22,46)	2	2
3	(78,20)	1	1
4	(96,66)	1.5	1.5
5	(25,95)	2.5	2
6	(10,50)	2	3
7	(63,34)	3	1
8	(32,48)	2	1.5
9	(75,79)	3	2.5
10	(31,26)	2.5	2
11	(93,34)	1.5	2.5
12	(20,8)	1.5	2
13	(81,61)	4	1.5
14	(55,68)	2.5	1
15	(13,35)	3	1
16	(12,9)	3	2.5
17	(27,15)	2	2
18	(16,77)	3.5	1
19	(53,23)	2	1
20	(39,65)	1.5	1.5

about the 20 demand spots in the service area is summarized in Table I. Each logistics distribution center is equipped with two vehicles for distribution services. The distribution volume of demand spot i is $v_{mi}(t)$, and the maximum vehicle traveling distance to complete a distribution service is 120km.

Simulation experiments are performed to assess the feasibility of applying C-IAPSO to solve vehicle path optimization of multiple distribution centers. The algorithm program is written in C++ language. The experimental experiment is configured as follows: Windows 10 operating syste, Intel Core i5 2.2GHz Central Processing Unit (CPU), Visual Studio 2013 compiling environment, and MATLAB 2015b simulation software. GA, IA, PSO, Comprehensive Learning PSO (CLPSO), and Adaptive PSO (APSO) are included for comparison to intuitively elaborate on the effectiveness of C-IAPSO. APSO possesses a fast convergence global searchability. CLPSO provides outstanding performances in multimodal optimization problems and maintaining swarm diversity.

To assess the performance of C-IAPSO, seven standard test functions are selected for comparison experiments, namely:

$$\text{Sphere}: f_1(x) = \sum_{i=1}^{n} x_i^2, \quad (-100 \le x_i \le 100) \tag{19}$$

$$\text{Quadric}: f_2(x) = \sum_{i=1}^{n} \left(\sum_{j=1}^{i} x_j \right)^2, \quad (-100 \le x_i \le 100) \tag{20}$$

$$\text{Ackley}: f_3(x) = -20 \exp\left\{-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}\right\} - \exp\left\{\frac{1}{n}\sum_{i=1}^{n}\cos(2\pi x_i)\right\} + 20 + e, \quad (-32 \le x_i \le 32) \tag{21}$$

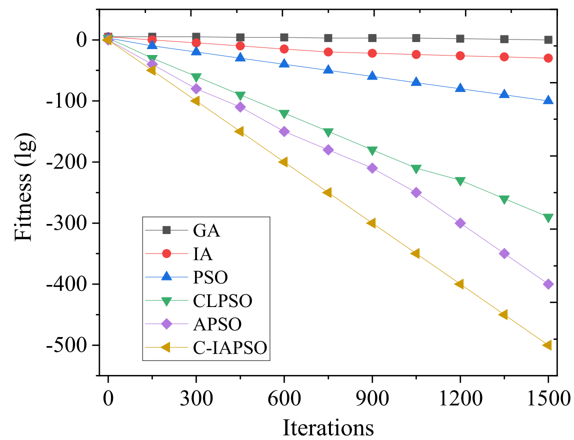

Fig. 5. Algorithm convergence curves on the sphere function.

$$\text{Griewank}: f_4(x) = \frac{1}{4000}\sum_{i=1}^{n} x_i^2 - \prod_{i=1}^{\pi}\cos\left(\frac{x_i}{\sqrt{i}}\right) + 1, \times (-600 \le x_i \le 600) \tag{22}$$

$$\text{Rastrigin}: f_5(x) = \sum_{i=1}^{i}\left[x_i^2 - 10\cos(2\pi x_i) + 10\right], \times (-5.12 \le x_i \le 5.12) \tag{23}$$

$$\text{Rosenbrock}: f_6(x) = \sum_{i=1}^{i}\left(100\left(x_{i+1} - x_i^2\right)^2 + (x_i - 1)^2\right), \times (-10 \le x_i \le 10) \tag{24}$$

$$\text{Schaffer}: f_7(x, y) = 0.5 + \frac{\left(\sin^2\sqrt{x^2 + y^2} - 0.5\right)}{1 + 0.001\left(x^2 + y^2\right)^2}, \times (-100 \le x_i \le 100) \tag{25}$$

Suppose that the particle swarm size is $N = 30$, the maximum iteration time is 1,500, the concentration threshold is $T_D = 0.3$, and the initial value of w is 1, which reduces to 0 with iterations linearly, $c_1 = c_2 = 1.4$. The experiment is repeated 10 times.

IV. RESULTS AND DISCUSSIONS

A. Simulation Result Analysis of C-IAPSO

Seven standard test functions $f_1 \sim f_7$ are selected for comparison experiments. Convergence curves are drawn on these functions to intuitively display the effects of different path optimization algorithms, as in Figure 5 to Figure 11. Compared with other algorithms, C-IAPSO improves the accuracy and stability. On the unimodal functions Sphere and Quadric, the accuracy of the C-IAPSO solution gets improved significantly. On the multimodal functions Ackley and Rosenbrock, the improvement in C-IAPSO accuracy is not that significant, with little difference from APSO. On the Schaffer function, the stability of C-IAPSO gets improved significantly, and all algorithms can converge to the same fitness value in the first 50 iterations. In subsequent iterations, the global optimal solution remains unchanged. Hence, the six algorithms present the same solution performance on the Schaffer function.

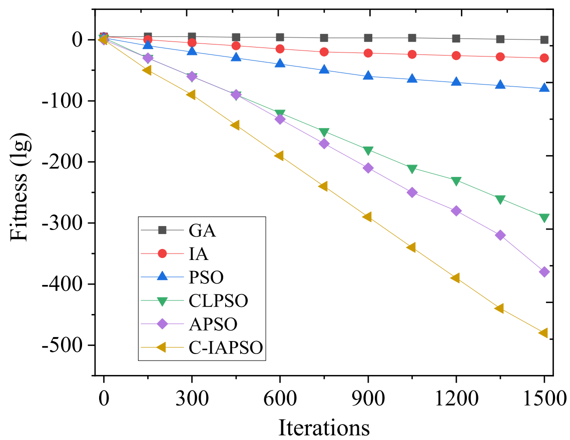

Fig. 6. Algorithm convergence curves on the quadric function.

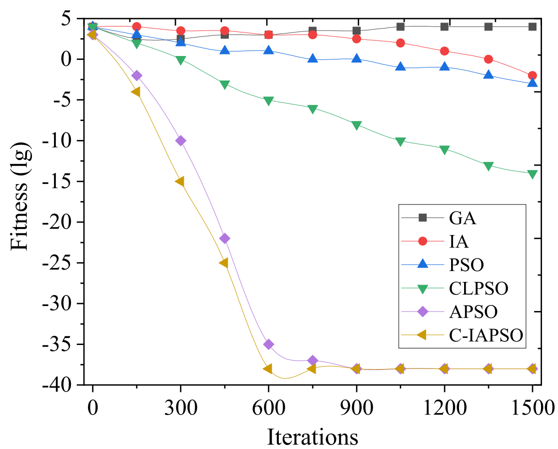

Fig. 7. Algorithm convergence curves on the ackley function.

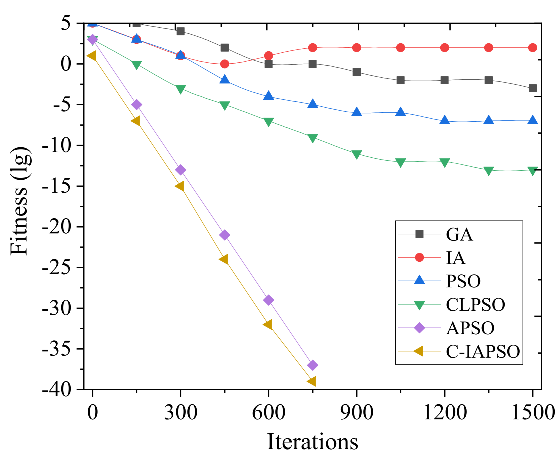

Fig. 8. Algorithm convergence curves on the griewank function.

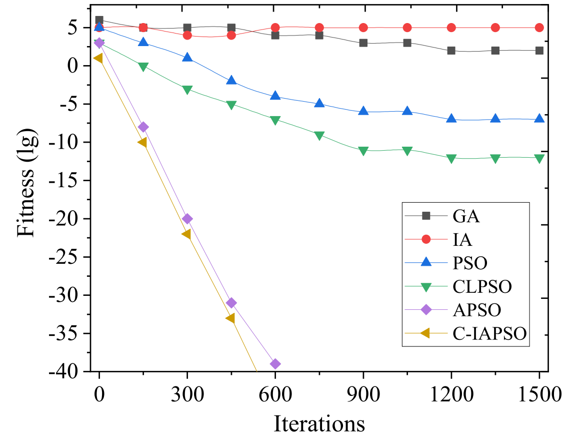

Fig. 9. Algorithm convergence curves on the rastrigin function.

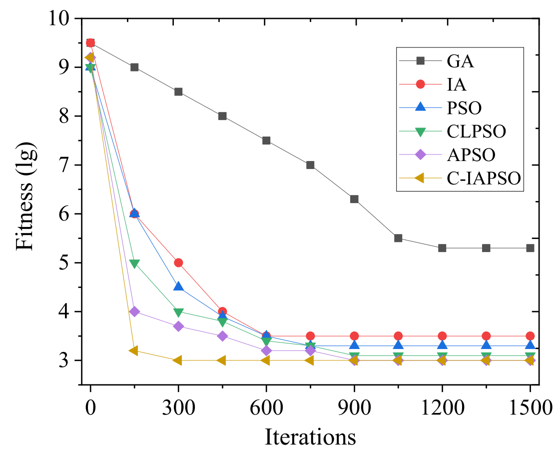

Fig. 10. Algorithm convergence curves on the rosenbrock function.

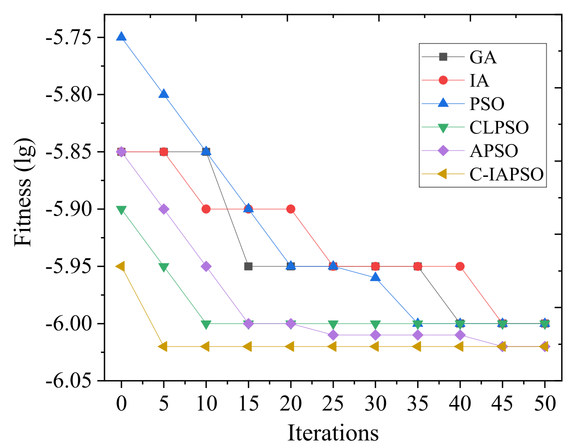

Fig. 11. Algorithm convergence curves on the schaffer function.

The above results suggest that C-IAPSO provides a faster convergence rate than the other five algorithms on both unimodal and multimodal functions, finding the global optimal in fewer iterations. Hence, C-IAPSO is suitable for solving vehicle path optimization of minimal cost. Feng *et al.* developed a GA and a lower bound algorithm (LB) to solve the scheduling problem of urban transport [35]. The GA can obtain an approximate optimal solution in almost all test cases with an average gap of 10.17 % compared with the LB, and the average calculation time of the algorithm is only 0.93% of CPLEX. Therefore, GA can be combined with the path optimization algorithm proposed here to solve the problems in actual logistics distribution.

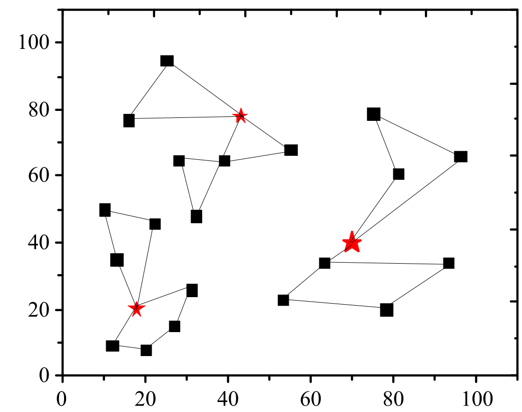

Fig. 12. The optimal distribution path obtained by C-IAPSO.

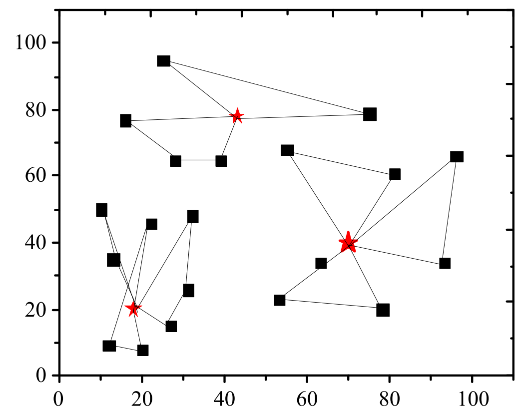

Fig. 14. The optimal distribution path obtained by APSO.

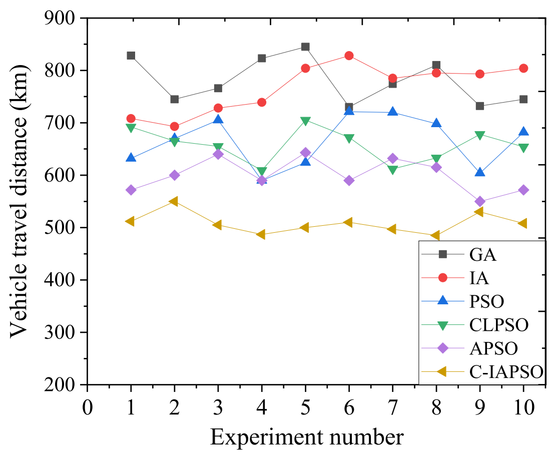

Fig. 13. Total vehicle traveling distances under the optimal distribution paths obtained by different algorithms.

B. Vehicle Path Optimization of Multiple Distribution Centers Based on C-IAPSO

On the issue of path optimization, Stopka *et al.* pointed out that it was important to state that relevant distribution tasks can be expressed in a form of graphs on specified transport networks, and thereby used the individual techniques of graph theory [36]. C-IAPSO is utilized for limited iterative calculations on the problem instance, and the obtained optimal path solutions are demonstrated in Figure 12. Using C-IAPSO for 10 repeated experiments, the optimal distribution path is obtained. Under this path, the vehicle travels 508.40km in total. C-IAPSO takes 3.07s for calculation on average. Under the same situation, the optimal distribution paths obtained by the other five algorithms are illustrated to compare the vehicle traveling distance, as in Figure 13.

Regarding the other five algorithms, the vehicle travels the shortest distance under the optimal distribution path obtained by APSO (Figure 14), totaling 600.40km; nevertheless, this is longer than the 503.22km of C-IAPSO. As shown in Figure 13, C-IAPSO is strongly stable in 10 repeated experiments; in contrast, GA and IA present poor stability, and the experimental results are quite different. The above results prove that C-IAPSO can provide strong global convergence and optimization ability for logistics distribution path optimization of multiple distribution centers, avoiding the premature phenomenon. Meanwhile, the algorithm's convergence rate and solution accuracy get improved in the later operation stage.

V. Conclusion

An expanding e-commerce industry size increases the demand for logistics distribution services from all transaction parties. The intelligent routing algorithm can automatically match vehicle data with path information, distribution destination, and product specifications; eventually, it can formulate the optimal distribution path that meets the actual needs.

Regarding the actual situation of rail transportation, the routing problem of distribution vehicles is discussed. IA that solves path optimization is integrated with PSO and antibody concentration to design a novel C-IAPSO model that can find the global optimal solution as soon as possible and increase the swarm diversity. Computer programming implements the algorithm, and simulation experiments are performed to assess the performance of C-IAPSO. The experiment using the C-IAPSO algorithm has been repeated 10 times to obtain the optimal distribution path. The total distance of vehicles traveling under the optimal path is 508.40km, and the average operation time of the algorithm is 3.07 seconds. Results demonstrate that C-IAPSO can provide the fastest convergence rate and the strongest optimization ability on different standard test functions. Vehicles travel the shortest distance in total under the optimal distribution path provided by C-IAPSO considering actual routing conditions.

The proposed C-IAPSO can reference logistics distribution companies in improving distribution efficiency and reducing transportation costs. While solving actual VRPs, the distribution path indicates not only the vehicle traveling distance but also the distribution time and transportation cost, which shall be determined based on specific research problems. Hence, other factors of distribution path optimization will be refined in the future.

References

[1] P. K. Sharma, N. Kumar, and J. H. Park, "Blockchain-based distributed framework for automotive industry in a smart city," *IEEE Trans. Ind. Informat.*, vol. 15, no. 7, pp. 4197–4205, Jul. 2019.

[2] Z. Lv, B. Hu, and H. Lv, "Infrastructure monitoring and operation for smart cities based on IoT system," *IEEE Trans. Ind. Informat.*, vol. 16, no. 3, pp. 1957–1962, Mar. 2020.

[3] C.-C. Lin and J.-W. Yang, "Cost-efficient deployment of fog computing systems at logistics centers in industry 4.0," *IEEE Trans. Ind. Informat.*, vol. 14, no. 10, pp. 4603–4611, Apr. 2018.

[4] K.-C. Chang, K.-C. Chu, H.-C. Wang, Y.-C. Lin, and J.-S. Pan, "Agent-based middleware framework using distributed CPS for improving resource utilization in smart city," *Future Gener. Comput. Syst.*, vol. 108, pp. 445–453, Jul. 2020.

[5] Y. P. Tsang, C. H. Wu, H. Y. Lam, K. L. Choy, and G. T. S. Ho, "Integrating Internet of Things and multi-temperature delivery planning for perishable food E-commerce logistics: A model and application," *Int. J. Prod. Res.*, vol. 59, no. 5, pp. 1534–1556, Mar. 2021.

[6] H. Treiblmaier, "Combining blockchain technology and the physical internet to achieve triple bottom line sustainability: A comprehensive research agenda for modern logistics and supply chain management," *Logistics*, vol. 3, no. 1, p. 10, Feb. 2019.

[7] Y. Li, F. Chu, C. Feng, C. Chu, and M. Zhou, "Integrated production inventory routing planning for intelligent food logistics systems," *IEEE Trans. Intell. Transp. Syst.*, vol. 20, no. 3, pp. 867–878, Mar. 2019.

[8] K.-F. Chu, A. Y. S. Lam, and V. O. K. Li, "Dynamic lane reversal routing and scheduling for connected and autonomous vehicles: Formulation and distributed algorithm," *IEEE Trans. Intell. Transp. Syst.*, vol. 21, no. 6, pp. 2557–2570, Jun. 2020.

[9] A. A. R. Hosseinabadi, A. Slowik, M. Sadeghilalimi, M. Farokhzad, M. B. Shareh, and A. K. Sangaiah, "An ameliorative hybrid algorithm for solving the capacitated vehicle routing problem," *IEEE Access*, vol. 7, pp. 175454–175465, 2019.

[10] L. Wang and J. Lu, "A memetic algorithm with competition for the capacitated green vehicle routing problem," *IEEE/CAA J. Automatica Sinica*, vol. 6, no. 2, pp. 516–526, Feb. 2019.

[11] J. Wang, T. Weng, and Q. Zhang, "A two-stage multiobjective evolutionary algorithm for multiobjective multidepot vehicle routing problem with time Windows," *IEEE Trans. Cybern.*, vol. 49, no. 7, pp. 2467–2478, Jul. 2019.

[12] O. Ozturk and J. Patrick, "An optimization model for freight transport using urban rail transit," *Eur. J. Oper. Res.*, vol. 267, no. 3, pp. 1110–1121, Jun. 2018.

[13] Z. Jiang, J. Gu, W. Fan, W. Liu, and B. Zhu, "Q-learning approach to coordinated optimization of passenger inflow control with train skip-stopping on a urban rail transit line," *Comput. Ind. Eng.*, vol. 127, pp. 1131–1142, Jan. 2019.

[14] C. Qi and L. Hu, "Optimization of vehicle routing problem for emergency cold chain logistics based on minimum loss," *Phys. Commun.*, vol. 40, Jun. 2020, Art. no. 101085.

[15] Y.-N. Guo, J. Cheng, S. Luo, D. Gong, and Y. Xue, "Robust dynamic multi-objective vehicle routing optimization method," *IEEE/ACM Trans. Comput. Biol. Bioinf.*, vol. 15, no. 6, pp. 1891–1903, Nov. 2018.

[16] G. Qin, F. Tao, and L. Li, "A vehicle routing optimization problem for cold chain logistics considering customer satisfaction and carbon emissions," *Int. J. Environ. Res. Public Health*, vol. 16, no. 4, p. 576, Feb. 2019.

[17] Z. Zhang, H. Qin, and Y. Li, "Multi-objective optimization for the vehicle routing problem with outsourcing and profit balancing," *IEEE Trans. Intell. Transp. Syst.*, vol. 21, no. 5, pp. 1987–2001, May 2020.

[18] D. Li, L. Deng, and Z. Cai, "Intelligent vehicle network system and smart city management based on genetic algorithms and image perception," *Mech. Syst. Signal Process.*, vol. 141, Jul. 2020, Art. no. 106623.

[19] M. Irfan *et al.*, "Optical-interference mitigation in visible light communication for intelligent transport systems applications," *Energies*, vol. 13, no. 19, p. 5064, Sep. 2020.

[20] A. Bucchiarone, S. Battisti, T. G. Dias, and P. Feldman, "Guest editorial diversification in urban transportation systems and beyond: Integrating people and goods for the future of mobility," *IEEE Trans. Intell. Transp. Syst.*, vol. 22, no. 4, pp. 2008–2012, Apr. 2021.

[21] H. Sun, J. Wu, H. Ma, X. Yang, and Z. Gao, "A bi-objective timetable optimization model for urban rail transit based on the time-dependent passenger volume," *IEEE Trans. Intell. Transp. Syst.*, vol. 20, no. 2, pp. 604–615, Feb. 2019.

[22] C. Cleophas, C. Cottrill, J. F. Ehmke, and K. Tierney, "Collaborative urban transportation: Recent advances in theory and practice," *Eur. J. Oper. Res.*, vol. 273, no. 3, pp. 801–816, Mar. 2019.

[23] B. Zhao, H. Gui, H. Li, and J. Xue, "Cold chain logistics path optimization via improved multi-objective ant colony algorithm," *IEEE Access*, vol. 8, pp. 142977–142995, 2020.

[24] J. Xie, L. R. G. Carrillo, and L. Jin, "An integrated traveling salesman and coverage path planning problem for unmanned aircraft systems," *IEEE Control Syst. Lett.*, vol. 3, no. 1, pp. 67–72, Jan. 2019.

[25] M. B. Ghorbel, D. Rodríguez-Duarte, H. Ghazzai, M. J. Hossain, and H. Menouar, "Joint position and travel path optimization for energy efficient wireless data gathering using unmanned aerial vehicles," *IEEE Trans. Veh. Technol.*, vol. 68, no. 3, pp. 2165–2175, Mar. 2019.

[26] J. Ji, A. Khajepour, W. W. Melek, and Y. Huang, "Path planning and tracking for vehicle collision avoidance based on model predictive control with multiconstraints," *IEEE Trans. Ultrason. Eng.*, vol. 66, no. 2, pp. 952–964, Feb. 2017.

[27] T. Berglund, A. Brodnik, H. Jonsson, M. Staffanson, and I. Söderkvist, "Planning smooth and obstacle-avoiding B-spline paths for autonomous mining vehicles," *IEEE Trans. Autom. Sci. Eng.*, vol. 7, no. 1, pp. 167–172, Jan. 2010.

[28] Q. Lin *et al.*, "A hybrid evolutionary immune algorithm for multiobjective optimization problems," *IEEE Trans. Evol. Comput.*, vol. 20, no. 5, pp. 711–729, Oct. 2016.

[29] C.-Y. Ho, T.-E. Lee, and C.-H. Lin, "Optimal placement of fault indicators using the immune algorithm," *IEEE Trans. Power Syst.*, vol. 26, no. 1, pp. 38–45, Feb. 2011.

[30] R. B. A. Koad, A. F. Zobaa, and A. El-Shahat, "A novel MPPT algorithm based on particle swarm optimization for photovoltaic systems," *IEEE Trans. Sustain. Energy*, vol. 8, no. 2, pp. 468–476, Apr. 2017.

[31] T. S. Babu, J. P. Ram, T. Dragičević, M. Miyatake, F. Blaabjerg, and N. Rajasekar, "Particle swarm optimization based solar PV array reconfiguration of the maximum power extraction under partial shading conditions," *IEEE Trans. Sustain. Energy*, vol. 9, no. 1, pp. 74–85, Jan. 2018.

[32] B. Y. Qu, P. N. Suganthan, and S. Das, "A distance-based locally informed particle swarm model for multimodal optimization," *IEEE Trans. Evol. Comput.*, vol. 17, no. 3, pp. 387–402, Jun. 2013.

[33] Y. Cao, H. Zhang, W. Li, M. Zhou, Y. Zhang, and W. A. Chaovalitwongse, "Comprehensive learning particle swarm optimization algorithm with local search for multimodal functions," *IEEE Trans. Evol. Comput.*, vol. 23, no. 4, pp. 718–731, Aug. 2019.

[34] W. T. Elsayed, Y. G. Hegazy, M. S. El-bages, and F. M. Bendary, "Improved random drift particle swarm optimization with self-adaptive mechanism for solving the power economic dispatch problem," *IEEE Trans. Ind. Informat.*, vol. 13, no. 3, pp. 1017–1026, Jun. 2017.

[35] X. Feng *et al.*, "Crowdsource-enabled integrated production and transportation scheduling for smart city logistics," *Int. J. Prod. Res.*, vol. 59, no. 7, pp. 2157–2176, 2020.

[36] O. Stopka, K. Jeřábek, and M. Stopková, "Using the operations research methods to address distribution tasks at a city logistics scale," *Transp. Res. Procedia*, vol. 44, pp. 348–355, 2020.

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