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# LOGISTICS PATH PLANNING BASED ON IMPROVED PARTICLE SWARM OPTIMIZATION ALGORITHM

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**Abstract.** In order to solve the problem of vehicle path scheduling management more reasonably, the author proposes a logistics path planning research based on improved particle swarm optimization algorithm. The author introduces a particle swarm optimization algorithm that incorporates a dynamic monkey jumping mechanism. Initially, dynamic population grouping is used to assign varying dynamic inertia weights, enhancing the algorithm's speed. Subsequently, the monkey jumping mechanism is added to ensure global convergence. This enhanced algorithm was then tested on two logistics distribution path optimization scenarios. In a consistent environment, the improved algorithm outperformed the standard particle swarm optimization algorithm by achieving a better optimal path fitness value, shorter average operation time, and a higher number of successful attempts to find the optimal solution. The experimental results show that out of 10 instances solved using the improved algorithm, 5 times obtained the optimal solution of 67.1km, and the optimal delivery path corresponding to the optimal solution was 0-4-7-6-0; 0-2-8-5-3-1-0, with an average calculation time of 1.26s, indicating high computational efficiency. The total delivery distance and average calculation time of the particle swarm algorithm, as well as the number of times to obtain the optimal solution, are 69.01, 2.7, and 3, respectively. It is evident that the enhanced particle swarm optimization algorithm significantly outperforms the conventional particle swarm algorithm. The improvements not only accelerate the optimization process but also enhance the algorithm's convergence, ensuring high-quality optimization results. Consequently, this improved algorithm holds substantial application value.

**Key words:** Particle swarm, Logistics distribution, Monkey jumping, weight coefficient

**1. Introduction.** In today's rapidly growing era of Internet e-commerce, logistics services have increasingly become an essential part of daily life [1]. Delivery, as the most important link in the entire logistics service process, has become a key goal pursued by various logistics companies with high performance time and low cost loss. A reasonable logistics distribution path can not only strengthen the core competitiveness of enterprises, but also provide a catalyst for the better and faster development of society [2].

The development of the logistics industry has become an important factor affecting the growth of a country's GDP. Reasonable planning of logistics performance plans to reduce distribution costs will bring huge economic and social benefits to the country [3-4]. In contemporary logistics, distribution serves as a crucial link that directly connects to consumers and represents the highest cost component in the entire logistics service process. Efficient distribution path planning, characterized by "high timeliness service and low cost loss," directly enhances the core competitiveness of enterprises. In today's logistics management, an optimized distribution route can significantly improve user experience through faster fulfillment times, while also reducing operational costs for enterprises by effectively managing distribution expenses; Optimizing logistics distribution paths can also help address societal issues like emission pollution and road congestion. This optimization fosters the alignment of resources, environment, and value within the country, promoting comprehensive sustainable development. Consequently, logistics path planning optimization has increasingly become a major research focus, attracting significant investment from experts, scholars, consulting firms, and related enterprises [5].

**2. Literature Review.** The problem of logistics vehicle path planning was first proposed in 1959 and has received great attention and extensive research from scholars and experts in various fields such as logistics science, operations research, combinatorial mathematics, and network planning [6]. In recent decades, experts across various fields have made substantial research advancements, exploring numerous problem scenarios and models. Consequently, a variety of solution methods have continuously emerged. Cai et al. introduced a heuristic elastic particle swarm optimization algorithm. In this approach, the A* algorithm offers global guidance for path planning in large-scale grids, while the elastic PSO algorithm employs contraction operations to

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identify the global optimal path from local optimal nodes, allowing particles to converge rapidly. In addition, during the iteration process, the rebound operation ensures the diversity of particles. The author maintains particle diversity through a rebound operation. Computer simulations and experimental results demonstrate that this algorithm not only overcomes the A* algorithm's limitation of not generating the shortest path, but also avoids the issue of failing to converge to the global optimal path due to a lack of heuristics [7]. Wang et al. proposed a dual layer search particle swarm optimization algorithm. This algorithm groups particle populations and variable dimensions, derives sub objective functions, constructs a double-layer search space, defines dynamic parameter matrices, and achieves information exchange and spatial reconstruction in the subspace. For optimization problems with complex features, double-layer search can achieve alternating fine search and rough search, thereby reducing computational costs and improving optimization efficiency [8]. Sun, H. et al. proposed a source optimization (SO) method that combines particle swarm optimization with a genetic algorithm (PSO-GA). This hybrid approach iteratively determines the optimal intensity distribution of the source. In this method, the pixelated source is decoded as an optimization variable for the optimal value function in the SO model. The PSO-GA algorithm, as an effective hybrid solution, converts the discrete SO problem into an optimal search for the value function, thereby enhancing lithography imaging performance in reverse [9].

The main goal of the author is to provide reliable support for logistics enterprises in route decision-making solutions, achieve cost reduction and efficiency improvement, and thereby enhance their market competitiveness. In recent years, many scholars have used particle swarm optimization to optimize problems such as neural network training and power system control, while the vehicle path planning problem, as a classic problem in the field of combinatorial optimization, has been relatively less optimized by this technology. Therefore, based on the establishment of a mathematical model for vehicle routing problems, the author proposes an improved particle algorithm that can effectively improve algorithm performance to solve the problem, ultimately improving solution quality and reducing logistics and distribution costs. The author's research not only enriches the solution schemes for optimizing logistics path planning problems, but also provides a foundation for future scholars to continue studying problems in this field, with rich theoretical and practical significance.

## 3. Method.

**3.1. Introduction to Particle Swarm Optimization Algorithm.** Particle Swarm Optimization (PSO) is a stochastic intelligent optimization algorithm inspired by population behavior, first introduced by Eberhart and Kennedy. This algorithm, categorized as a natural evolutionary algorithm, was developed by mimicking the swarming behaviors of organisms like insects, birds, animals, and fish [10-11]. After research, it was found that these biological populations share the common characteristic of being able to search for food in a certain cooperative way, and continuously evolve and change their search patterns by learning their own experience and the experience of other individual members, ultimately moving closer to the region containing the global optimal solution. The particle swarm optimization algorithm has demonstrated its superiority in solving practical problems due to its simple steps and low implementation cost. It has gradually become a key focus and research object for scholars in the field of intelligent optimization.

**3.2. Process of Particle Swarm Optimization.**

*Initialization:* Start by randomly assigning speeds and positions to a population of particles while setting necessary parameters [12].

*Evaluation:* Assess the fitness value of each particle in the population, initiating the evolutionary process.

*Local Optimization:* Evaluate the fitness of each particle and compare it with its historical best fitness. If an improvement is found, update the particle's position accordingly.

*Global Optimization:* Compare each particle's current best fitness with the global best fitness. If a particle achieves a better fitness, update the global best position.

*Velocity and Position Update:* Adjust the velocity and position of each particle based on its previous state and the best positions found so far.

*Termination Check:* Check if the termination condition is met. If not, repeat steps 2 to 5. If yes, end the process. This process forms the basic flow of the PSO algorithm, aiding in understanding its operation (Figure 3.1).

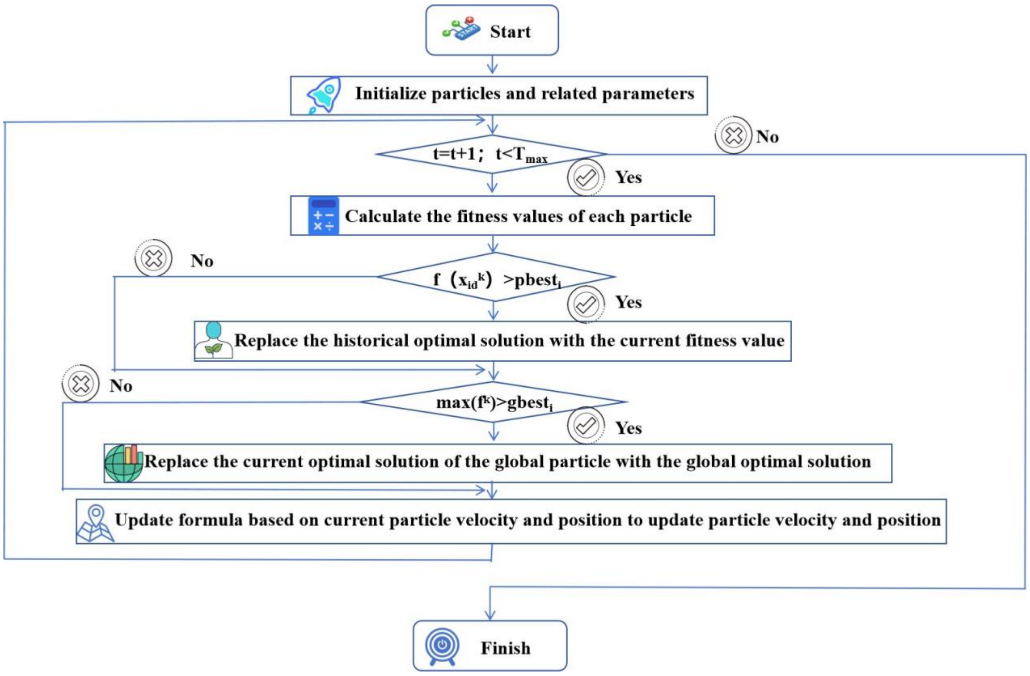


Fig. 3.1: Flowchart of the original PSO algorithm

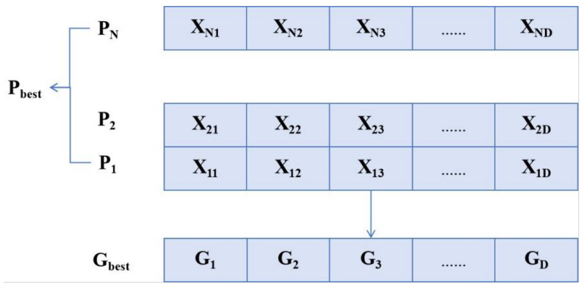


Fig. 3.2: Pbest Guided Gbest's Dimensional Learning Strategy Model

**3.3. Dimension wise learning strategies.** At present, in most studies, the strategy of selecting all dimensions to update and re evaluate the optimal particle guidance in the population as a whole is adopted. However, for complex multi-dimensional function optimization problems, using this method may mask the information of certain correct evolutionary dimensions due to the interference between dimensions, resulting in a waste of evaluation times and reducing the convergence speed and efficiency of the algorithm [13]. The dimension by dimension learning strategy separates the optimal solution and the learning object in dimensions, independently examining the information in each dimension, which can effectively avoid the problem of inter dimensional interference. In PSO, as the population evolves, the Pbest of each particle is constantly updated, recording and updating its historical best performance during flight, with high utilization value. Therefore, in order to ensure the diversity and effectiveness of learning objects in the dimension wise strategy, the author proposes a Pbest guided Gbest dimension wise learning strategy based on the characteristics of Pbest and the advantages of dimension wise strategy.

Figure 3.2 shows a schematic diagram of the model for this strategy. The figure introduces the push and push operations in the data structure to simulate the actions of all Pbest in the population to guide the optimal particles one by one.

The idea of this strategy is to decompose the position vectors of Gbest and Pbest by dimension, and combine the values of one dimension on Pbest with the values of other dimensions on Gbest to form a new Gbest; New solution for evaluating fitness values; If the current new solution has better quality, retain the update result of Pbest dimension information on the solution; Otherwise, abandon the current dimension value and keep the original Gbest dimension information unchanged. Adopt this greedy evaluation method until all dimensions are updated. After all the dimensions of a Pbest have been guided by the corresponding dimensions of Gbest, a stack exit operation is performed to leave the Pbest stack container and compress it, starting the guidance of other Pbest on Gbest [14].

By introducing a greedy evaluation strategy into the dimension by dimension learning strategy, the degradation of certain dimensions is completely eliminated, avoiding the problem of masked evolutionary dimension information, and thus obtaining higher quality solutions, significantly improving convergence accuracy. Meanwhile, unlike most dimension wise learning strategies that use the method of learning from a single object, the Gbest in this strategy is influenced by the guidance of the population individual Pbest, strengthening the connection between the individual optimal particle and the population optimal particle, and improving the diversity of the learning objects for the optimal particle [15,16].

**3.4. Corrective Strategies.** In traditional PSO, particles are updated according to their velocity and displacement during the evolution process. They are guided by individual best and group best during the evolution process, lacking attention to the entire motion process of particles. Especially in complex multimodal functions with high optimization difficulty, particles generate a lot of randomness during the evolution process, which is one of the important reasons for the slow convergence speed of particle swarm optimization algorithms. During population evolution, particles might initially move towards the optimal solution direction. However, due to the intricacies of optimization, subsequent generations might deviate from this path. At this time, if we continue to follow the update speed and displacement, guided by the error information generated by the random flight of some particles from the previous generation, it will inevitably waste particle learning time, leading to a slower convergence speed. In order to address this issue, the author proposes a correction strategy that intervenes in the optimization direction of the next generation of particles by monitoring the changes in their motion direction throughout the evolution process, in order to avoid further erroneous guidance and improve the convergence speed of the population. Figure 3.3 provides a simple schematic diagram of the correction strategy. The A-class particles in the figure represent particles that have been affected by randomness and incorrect guidance. The next generation update will deviate from the direction of the optimal solution, and the update speed will be reversed by taking the direction of the velocity vector, so that the next generation can move towards the direction of the optimal solution and improve the convergence speed; Meanwhile, B-class particles with the correct direction of motion will continue to be updated in the original way [17].

In the algorithm, each particle represents a potential solution to the problem, and the optimal solution is derived by considering both the current and historical best solutions. During each iteration of the particle swarm, particles update themselves based on the best solutions they have encountered. At each iteration, the velocity of the particles is updated using equation 3.1:

$$v_{ik}^{g+1} = Wv_{ik}^{g} + \sigma_1 r_1 (S_{ak}^{g} - S_{ik}^{g}) + \sigma_2 r_2 (S_{bk}^{g} - S_{ik}^{g}) \tag{3.1}$$

In the formula: $\sigma_1$ and $\sigma_2$ are the initialization acceleration constants; g is the particle swarm update algebra; In addition, $r_1$ and $r_2$ are two mutually independent random functions; w is a weight factor variable; $v_i$ is the running speed of the current particle. When the particle swarm is iterated each time, its position is updated by equation 3.2:

$$S_{ik}^{g+1} = S_{ik}^{g} + v_{ik}^{g+1} \tag{3.2}$$

**3.5. Establishment of a mathematical model for optimizing logistics distribution paths.** If we want to deliver agricultural products to customers, assuming that the distance between customer i and customer j is represented by d(i,j) as i,j=0,1,$\cdots$M, and d(0,0) as the distribution center, based on the description of the logistics distribution path selection problem mentioned above, a mathematical model can be established as

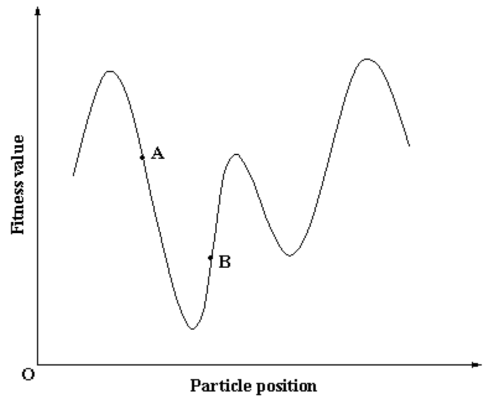


Fig. 3.3: 2D schematic diagram of correction strategy

follows:

$$Rou = \sum_{i=1}^{V}(\sum_{i=1}^{T} d(r_v^{j-1}, r_v^j) + d(r_v^T, 0)) \cdot sgnT \tag{3.3}$$

In the formula, $r_v^j$ represents the order of customers in the vehicle v delivery path as j; When referring to the variables T and V, T represents the total number of customers transported by a specific vehicle (v), while V denotes the total number of vehicles. If T equals 0, it indicates that the vehicle has no customers to transport, whereas a value of 1 for T signifies that the vehicle has customers to transport. The parameter sgn (T) satisfies equation 3.4:

$$sgn(T) = \begin{cases} 1 & (T \geqslant 1) \\ 0 & (T = 0) \end{cases} \tag{3.4}$$

The constraint conditions for route optimization are:

$$\begin{cases} C_{v1} \cap C_{v2} = \phi, v_1 \neq v_2 \\ \sum_{i=1}^{T} q_{r_v} \leqslant Q_v, T \neq 0 \\ \bigcup_{v=1}^{V} R_v = \{1, 2, \cdots, M\}, 0 \leqslant T \leqslant M \\ \sum_{j=1}^{T} d(r_v^{j-1}, r_v^j) + d(r_v^T, 0) \leqslant L_v, T \neq 0 \end{cases} \tag{3.5}$$

Its optimization objective function:

$$G_{min} = \partial Rou^{\beta} \tag{3.6}$$

In the formula, $C_v$ represents the set of customer points for vehicle v delivery; M is the total number of customers; $q_i$ is the demand for customer i; $Q_v$ is the maximum load capacity of vehicle v; $R_v$ is a collection of customer points for vehicle v delivery; $\partial$ is the weighted coefficient; $\beta$ is the amplification factor; $L_v$ is the maximum distance transported by the vehicle; $v_i$ is the set of vehicles that need to be used to transport customers [18]. According to equation 3.6, it can be concluded that logistics distribution not only requires fewer delivery vehicles, but also the shortest delivery path. It also requires delivering goods to customers within a specified time. This essentially involves finding an optimal logistics distribution route that satisfies multiple

Table 3.1: Environmental Data

| Serial Number | longitude/(°E) | latitude/(°N) | elevation/ |
|---|---|---|---|
| 0 | 117.2090576 | 39.11549092 | 1.635 |
| 1 | 117.2091435 | 39.11549092 | 1.750 |
| 2 | 117.2092296 | 39.11549092 | 1.957 |
| 3 | 117.2093154 | 39.11549092 | 2.014 |

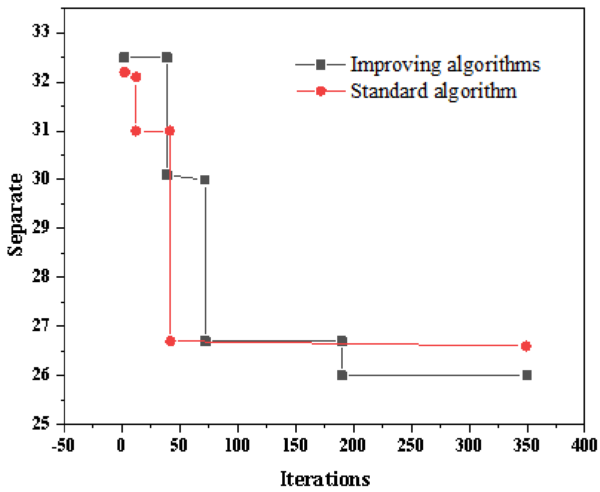


Fig. 4.1: Comparison of convergence speed between two algorithms

constraints simultaneously. The current particle swarm optimization algorithm simulates the foraging behavior of bird flocks and has parallel search capabilities. However, it has certain shortcomings, such as being trapped in local optima and slow maturation speed. In order to obtain a better logistics distribution path, it must be improved.

**3.6. Simulation Environment and Parameter Settings.** Use Google Earth to obtain geographic elevation data around a scenic area, and use ArcGIS to convert the features into grids as the logistics and transportation environment. Partial environmental elevation data is shown in Table 3.1.

*Experiment 1.* Logistics company has a distribution center with coordinates (0,0), which needs to deliver goods to customers at point coordinates (15,15). There are some buildings between them as shown in Table 1. The experimental hardware for simulation is: P5 dual core 2.9GCPU, 4GB memory, and 500G hard disk; The operating system is Windows 7 and the programming language is VC6.0++.

**4. Results and Discussion.** In the same environment, when comparing the convergence speed, the improved particle swarm algorithm's convergence process, as depicted in Figure 4, is noteworthy. Compared to the standard particle swarm algorithm, both algorithms exhibit rapid progress towards local optimal solutions. However, with increasing iterations, the standard particle swarm algorithm struggles to escape local optima. Conversely, the improved particle swarm algorithm, incorporating a dynamic monkey jumping mechanism, proves superior by generating 25 better solutions when the iteration count reaches 186. Hence, this mechanism effectively addresses the limitations of the standard particle swarm algorithm [19].

To evaluate the superiority of the enhanced particle swarm algorithm, we conducted comparative simulations with three other optimization algorithms: particle swarm algorithm, genetic algorithm, and ant colony

Table 4.1: Calculation Results of Improved Algorithm

| Calculation times | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | average |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Total delivery distance/km | 68.3 | 68.3 | 67.1 | 67.7 | 68.3 | 68.1 | 67.1 | 67.1 | 67.1 | 68.2 | 67.82 |
| Calculation time/s | 1.1 | 1.0 | 1.0 | 1.4 | 1.3 | 1.7 | 1.3 | 1.0 | 1.0 | 1.2 | 1.26 |

algorithm. Each algorithm underwent 100 runs, and the average outcome was considered the final result. Here are the simulation test results indicating the optimization success rates for each algorithm:Particle Swarm Algorithm,Genetic Algorithm,Ant Colony Algorithm,Improved Particle Swarm Algorithm.These results provide insights into the relative performance of each algorithm, highlighting the effectiveness of the enhanced particle swarm algorithm: The number of failures is 12, 5, 7, 3, the success rates are 88%, 95%, 93%, 97%, and the running time is 10, 4.2, 5.2, and 1.8 seconds, respectively. The comparison results show that the improved particle swarm optimization algorithm has increased the success rate of logistics distribution path optimization, increased the speed of the algorithm, and effectively prevented other algorithms from falling into local optima and premature convergence defects.

*Experiment 2.* A certain delivery problem requires delivery from a central warehouse to 8 customers. There are 2 vehicles in the central warehouse, each with a load capacity of 8 tons. The maximum driving distance for each delivery is 40 km, and the demand of each distributor is set to qi (i=1,2... 8) (unit: t). The distance between the distribution center and each distributor, the demand of customers, and the distance between the distribution center and customers, as well as between customers and customers (0 represents the distribution center, 1-8 represents 8 customer points). The parameter settings are the same as above, and the improved algorithm is used to run and solve 10 times. The calculation results of the total delivery distance and calculation time are shown in Table 4.1.

Out of 10 instances solved using the improved algorithm, 5 times obtained the optimal solution of 67.1km, and the optimal delivery path corresponding to the optimal solution was 0-4-7-6-0; 0-2-8-5-3-1-0, with an average calculation time of 1.26s, indicating high computational efficiency. The total delivery distance and average calculation time of the particle swarm algorithm, as well as the number of times to obtain the optimal solution, are 69.01, 2.7, and 3, respectively. The enhanced particle swarm algorithm clearly outperforms the standard particle swarm algorithm. Sensitivity analysis of the new algorithm reveals that the performance of traditional particle swarm optimization algorithms is greatly influenced by the choice of weight coefficients. Optimal weight coefficients typically fall within the range of [0.8, 1.2]. If the size of the weight coefficients is not selected properly, it directly leads to the algorithm not finding the appropriate optimal solution; The enhanced algorithm addresses the necessity for larger weight coefficients during the initial optimization stages to expedite convergence. As optimization progresses and approaches the optimal solution, weight coefficients gradually decrease, facilitating more precise solution refinement. This adaptive approach to weight coefficients influences the algorithm's performance across various optimization ranges and periods. However, compared to traditional particle swarm optimization methods, the improved algorithm demonstrates reduced sensitivity to the specific size of weight coefficients, indicating enhanced robustness and effectiveness. Through experiments, it is known that the reason why the improved particle swarm optimization algorithm outperforms other algorithms in terms of search performance and optimization path planning ability is mainly because the inertia weight factor of the improved particle swarm algorithm adaptively changes with the dynamic grouping of the group. Furthermore, the integration of the monkey jumping mechanism addresses the issue of "premature convergence," enhancing the efficiency of logistics distribution path exploration. This improvement enables faster discovery of optimal logistics distribution paths, thereby facilitating safe and efficient distribution in agricultural production processes. Simulation results affirm that the enhanced particle swarm optimization algorithm serves as an effective tool for optimizing logistics distribution paths [20].

**5. Conclusion.** The author introduces a study on logistics path planning using an enhanced particle swarm optimization algorithm. Addressing the limitations of existing heuristic algorithms in logistics distribution path optimization, the study proposes an algorithm leveraging an improved dynamic monkey jumping mechanism. Simulation outcomes demonstrate that this particle swarm optimization algorithm, enriched with a dynamic monkey jumping mechanism, enhances the success rate of logistics distribution path optimization, yielding superior solution outcomes and efficiency. These findings offer valuable insights for the exploration of other heuristic algorithms and logistics distribution path optimization challenges.

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