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Retraction

Retracted: Application of Improved Particle Swarm Optimization Algorithm in Logistics Energy-Saving Picking Information Network

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

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[1] X. Yu, "Application of Improved Particle Swarm Optimization Algorithm in Logistics Energy-Saving Picking Information Network," *Wireless Communications and Mobile Computing*, vol. 2022, Article ID 6411285, 8 pages, 2022.

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Research Article

Application of Improved Particle Swarm Optimization Algorithm in Logistics Energy-Saving Picking Information Network

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In order to solve the logistics optimization problem, an application method of the improved particle swarm optimization algorithm in logistics energy-saving pickup information network is proposed. Firstly, a mathematical model of logistics cycle picking information scheduling optimization is established, logistics and picking paths are encoded as particles, and the optimal logistics cycle picking optimization scheme is found through the cooperation between particles. Secondly, the deficiencies of the particle swarm optimization algorithm are improved accordingly. In order to test the performance of the IPSO algorithm in solving the logistics circulation picking problem, in the simulation environment of P42 core, 2.6 GHz CPU, 4 GB memory, and Windows XP, the simulation experiment was carried out using VC++6.0 programming operating system. The particle number of the IPSO algorithm is 20, $\omega_{\max} = 5$, $\omega_{\max} = 1$. The experimental results show that the improved particle swarm optimization algorithm can effectively bypass the premature convergence of the traditional particle swarm optimization algorithm and ensure that the optimal solution is searched in the global scope, and the optimal probabilistic solution is obtained, which is better than other scheduling algorithms, with more obvious advantages.

1. Introduction

In 1998, 0zcanh first attempt was made to improve the particle swarm optimization algorithm, and the particle trajectories in one-dimensional and multidimensional space were analyzed. In 2002, CLERC made a preliminary analysis of the particle convergence of the particle swarm optimization algorithm and found that the algorithm has some defects, but in the research of particle swarm optimization, the research on the first convergence is still of great significance [1]. The parameter constraints obtained in the research are still widely used in modern logistics algorithms. In 2003, Trealea simplified the particle swarm optimization model by using the discrete dynamic system theory and obtained a series of parameter selection conditions. The particle swarm optimization (PSO) algorithm is an evolutionary algorithm based on swarm intelligence. The PSO algorithm is similar to the genetic algorithm. It is also a public good; see Figure 1.

2. Literature Review

The particle swarm optimization algorithm is a public intelligent optimization algorithm jointly developed by American social psychologist Kennedy J and electrical engineer Eberhart RS, inspired by the predatory behavior of birds. The algorithm has the advantages of simplicity and few parameters, but after a certain number of iterations, the diversity of the population decreases rapidly, making the algorithm easy to locate. For example, Liang and Geng introduced the velocity formula and proposed a particle-by-particle optimization algorithm based on the inertial weight dynamic

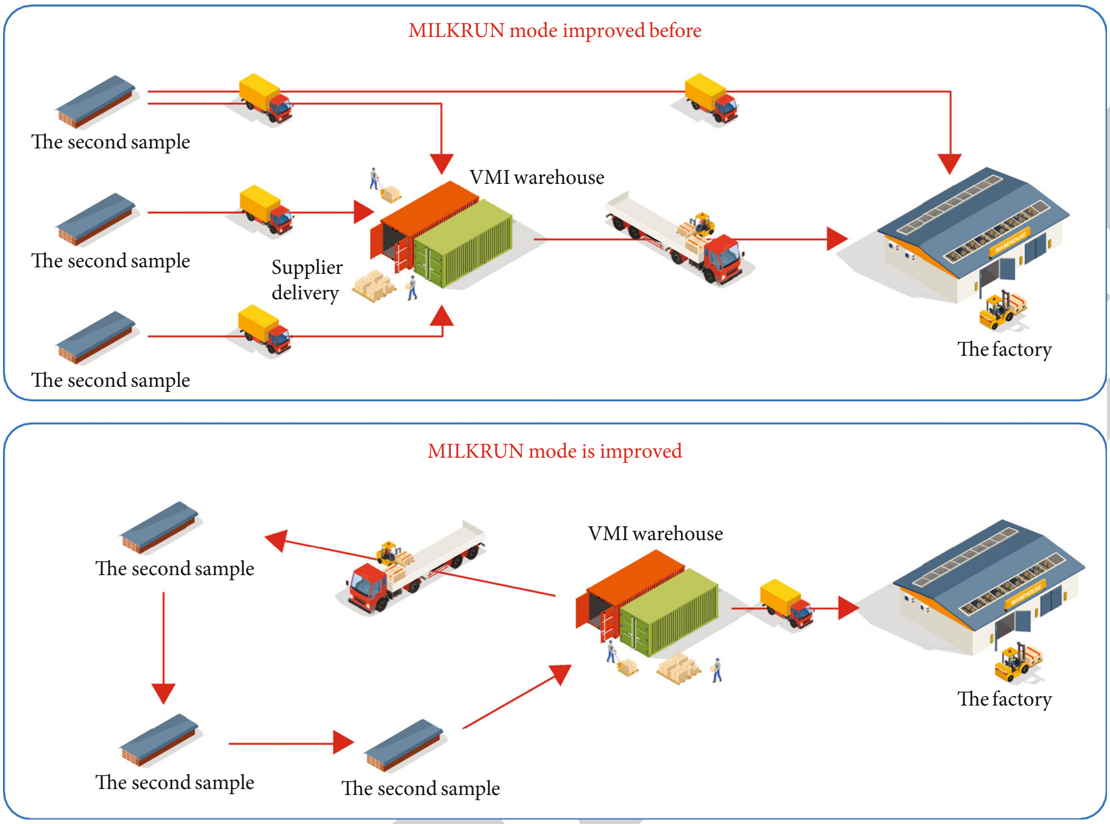


FIGURE 1: Cycle pickup scheme.

adaptive control of fuzzy systems [2]. In this paper, the particle swarm optimization algorithm based on the similarity exchange algorithm is used to solve the localization problem of the shredder.

As early as the 1960s, Hua and others proposed the vehicle logistics planning problem (VRP), and then, Chen and others first proposed the optimal mode of good distribution. The influencing factor is the number of target distribution points [3]. In the 1980s, Ke and others fully considered the time problem in the path decision-making of logistics distribution and added the time window to the mathematical model to achieve the goal of rapid distribution [4]. Then, Tian added a time window to the original VRP model to realize the path optimal solution with a time window [5]. In traditional logistics, two methods are generally used to solve the optimization problem. One is an exact algorithm for solving the path optimization problem. For example, Xiaoping et al. proposed a hybrid immune algorithm. The algorithm mixes the greedy algorithm and deletes the cross operator in the immune algorithm, which improves the search accuracy of the algorithm and can get a better global optimal solution [6]. Zhou and others proposed the hybrid greedy algorithm and added 2-opt local search strategy to the greedy algorithm. For the path optimization problem, the algorithm accelerated the convergence speed and produced the optimal solution in a short time [7]. Raj and Kannan proposed the insertion point at the 4/3 approximation of the distance matrix to study the reoptimization problem of the metric minimum path. In dealing with the reoptimization problem of the metric maximum path, they proposed the optimization algorithm of the insertion point at the 4/5 approximation of the distance matrix to optimize the path planning problem [8]. Ramaraju et al. proposed a hybrid particle swarm optimization algorithm to embed the championship selection method in evolutionary computing into PSO [9].

Building on existing research, this paper presents a study to improve logistics related to information network selection. The origin of the particle swarm optimization algorithm was inspired by bird feeding and human decision-making behavior. In PSO, birds are abstracted as having no volume and size; they are connected to d-dimensional space. For the performance of the IPSO algorithm in solving the problem of logistics recycling and picking up goods, under the simulation environment of P42 core, 2.6 GHz CPU, 4 GB memory, and Windows XP operating system, the simulation experiment is carried out by using VC++6.0 programming. The particle number of the IPSO algorithm is 20, $\omega_{\max} = 5$, $\omega_{\max} = 1$.

3. Optimization of Logistics Circular Picking Information Network Based on Improved Particle Swarm Optimization Algorithm

3.1. Overview of Particle Swarm Optimization Algorithm. The particle swarm optimization algorithm is also known as particle swarm optimization (PSO). In 1995, he studied bird hunting and developed a communication model. By studying this phenomenon, scientists have learned that data about individuals and groups of birds is shared [10]. For the convenience of theoretical research, "particles" are considered abstract substances, with only velocity and acceleration, but no mass and volume. Among them, "swarm" refers to the particle swarm that conforms to the principle of proximity, quality, diversity, stability, and adaptation. These five basic principles generally apply to the design of artificial life. PSO (particle swarm optimization) is similar to the genetic algorithm. These are large-scale intelligent optimization algorithms based on evolution. However, there are some differences between the two. The particle swarm optimization algorithm searches the optimal solution in the solution space, while the genetic algorithm searches the optimal value through cross mutation.

3.1.1. Principle of Particle Swarm Optimization Algorithm. The particle swarm optimization algorithm is derived from the intelligent population algorithm that simulates the movement and foraging behavior of birds. The model is based on the natural laws of flight (swimming) for birds (or fish). It is assumed that there is only one place with food in a known area, and a group of birds unite to find the only food. Initially, the birds were randomly distributed in this known area [11]. It is known that all birds in this area know the general direction and location of food but do not know the specific location of food. These birds are independent individuals. They neither compete nor cooperate. Birds can exchange information. Each bird can adjust its position appropriately according to the flight attitude of surrounding birds and follow the principles of keeping a certain distance from the nearest individuals around, flying to the center of the group, and avoiding deviation. Moreover, the group can form an evolutionary model by sharing social information, determine the best information of food currently obtained in the whole group, and then compare it with its own best information, so as to adjust its flight speed and position. When birds change their positions, they must exchange information and then adjust the best location of the population. This process continues to circulate until the food is finally found [12]. The particle swarm optimization algorithm forms a population intelligent optimization algorithm by using this model and adding mathematical properties such as speed, acceleration, and multidimensional search.

3.1.2. Performance Comparison with Other Algorithms. Select standard particle algorithm (PSO), genetic algorithm (GA), ant colony algorithm (ACO), and dynamic programming algorithm to compare with this algorithm. Each algorithm has 20 trials. Comparing the results of finding the optimal solution and the average solution time, the following conclusions can be drawn:

(1) Compared with the dynamic programming algorithm, the solution time of other algorithms is greatly reduced, which improves the efficiency of logistics distribution vehicle scheduling. This is mainly because the dynamic programming algorithm uses the exhaustive method to search for the optimal solution, and the number of optimization changes exponentially with the scale of the problem, which is not feasible in practical application

(2) Compared with other swarm intelligence algorithms, the success rate of the IPSO algorithm in finding the optimal solution increases, and the solution time also decreases. This is mainly because the IPSO algorithm reduces the number of iterations to find the optimal solution, reduces the workload, improves the research ability of the algorithm, and delivers better transportation

3.2. Improved Particle Swarm Optimization Algorithm. Particle swarm optimization (PSO) takes bird aggregation as the optimization goal and generally simulates the flight and foraging behavior of birds. In the PSO algorithm, the personal position, historical position, and global position of the entire particle swarm provide information for each particle, and the goal of finding a solution is to continuously delay the flight of a single particle in the policy space [13]. Although there is little research on the discrete domain, especially routing planning and combinatorial optimization, the particle swarm optimization algorithm has been successfully applied to solve continuous problems. Although the difference of the discrete quantity operation law is not considered, and there is a big gap with other algorithms, its definition speed is exchange list, and other quantities and algorithms are also defined. Similarly, using the law of exchange list, Huang Lan and others also defined different discrete operation rules. The algorithm is only simulated for the small dimension TSP problem. Nevertheless, his algorithm proves that PSO is feasible in solving discrete optimization problems and still shows its strong evolutionary characteristics.

3.2.1. Process of Improving Particle Swarm Optimization Algorithm. In view of the discovery that the PSO algorithm is easy to fall into refinement, low integration, and easy to diverge in the later stage of iteration, researchers at home and abroad have comprehensively improved the PSO algorithm, and it is huge. A lot of research has happened. According to the improved methods of the PSO algorithm, it is classified as follows:

(1) The innovation of different parameters in the particle swarm optimization algorithm mainly includes the transformation of inertia proportion, the update of learning factor, the selection of group size, and the setting of algorithm stop conditions

(2) Connect with different optimization algorithms, develop strengths and avoid weaknesses, and have key updates to form a hybrid algorithm

(3) In the innovation of method topology, its topology can be divided into global and local, which can be classified and improved according to these two

3.3. Parameter Analysis of Particle Swarm Optimization Algorithm. The main parameters of the particle swarm optimization algorithm include maximum particle velocity $V_{\max}$, maximum particle generation $G_{\max}$, the inertia weight ω of the particle itself, the population size m of the particle swarm, and the acceleration constants C_1 and C_2 selected when solving the problem.

$V_{\max}$ determines the distance that can be selected between the current position of the particle and the best position of the particle swarm. If $V_{\max}$ is too small, the particle has insufficient search ability for all regions, resulting in falling into the local optimal value. On the contrary, if $V_{\max}$ is too high, the particle may fly over the best solution. This restriction has three purposes to prevent calculation overflow, realize manual learning and attitude change, and determine the granularity of problem space search [14].

The inertia weight ω enables it to expand the searchable space of the current particle, maintain the inertia of particle motion, and enable the particle to explore new areas, which ensures that the particle can conduct a new search.

3.4. Application of Improved Particle Swarm Optimization Algorithm in This Paper. It can be seen from this paper that in the objective function of this paper, the inventory cost and transportation cost of the service center are determined by the recovery cycle of the service station, so the mathematical model is a nonlinear mixed integer optimization model [2].

A nonlinear programming problem is an NP-hard problem, and a nonlinear integer programming problem is one of nonlinear programming problems. Therefore, it must also be an NP-hard problem. The general complexity of traditional algorithms in solving the exact solution of NP-hard problems is exponential. The enumeration method, cutting plane method, and heuristic algorithm are general algorithms for solving nonlinear integer programming problems with small variables.

3.4.1. Enumeration Method

(1) Branch and Bound Method. When we are solving a problem with many constraints, we can simplify the problem first and transform problem B into problem A by reducing some constraints. When we solve the optimal solution of problem A, we can add some constraints to it, which reduce the possible solution of problem A and obtain the subproblem solution of problem B. When we continue to add constraints and finally all constraints are the same as problem B, problem A is transformed into problem B, and the solution of problem A is the solution of problem B. When solving a large number of combinatorial optimization problems, if the weight of each node is not estimated well, it is not much different from exhaustive search in extreme cases. When the number of solutions is large, even the current advanced calculation tools may not be able to solve [15]. The branch and bound method stores the bounds of many leaf nodes and the corresponding cost matrix. These measures will spend a lot of memory space.

(2) Complete Enumeration. The complete enumeration method is a method to enumerate and test all feasible solutions in the set of feasible solutions. Because the exact optimal value of the problem must be included in the range of feasible solutions, the most appropriate value of the problem can be found. The disadvantage of the complete enumeration method is that the calculation workload is very large. When the number of variables and constraints is large, the solution is almost impossible. Therefore, for the complete enumeration method, the problem that must be considered in the solution process is how to skillfully construct the enumeration process. At present, it is often used to turn the complete enumeration method into the partial enumeration method.

(3) Cutting Plane Method. The basic idea of using the cutting plane method to solve integer programming is to solve the optimal solution of the relaxation problem first. If the obtained solution is an integer solution, the solution ends. If not, add constraints, cut off the corresponding feasible region, and then solve again. The newly added constraints are used to cut off the partial noninteger solution of the relaxation problem and retain the integer solution, which is equivalent to cutting off the partial feasible region of the relaxation problem [16]. After multiple cuts, when there is a point on the feasible region of the relaxation problem and all the coordinates of this point are integers, then this vertex is the optimal solution to the problem. How to construct the cutting inequality is the key problem of the cutting plane method. Only by ensuring that no integer feasible solution is cut off after adding some constraints can the real cutting be achieved. Because of the slow convergence often encountered in the process of solving integer rule problems by the cutting plane method, it is still rare to use it to solve integer programming problems.

(4) Heuristic Algorithm. The heuristic algorithm is a method and strategy to find solutions to problems, which reflects people's subjective initiative and creativity, because it is based on experience and judgment. Heuristic algorithms can deal with NP-hard problems more effectively, but in order to give better play to the advantages and make up for the shortcomings of this algorithm, heuristic algorithms are often used together with other algorithms to achieve better results. The most widely used heuristic algorithms in academia today are: the genetic algorithm, simulation algorithm, neural network algorithm, particle swarm optimization algorithm, and ant colony intelligence algorithm [17]. In recent years, genetic algorithms have been widely used to solve the problem of center location in logistics networks. However, compared with particle swarm optimization, the genetic algorithm has many shortcomings and is difficult to implement. The particle swarm optimization algorithm solves faster, provides timely data, and has higher conversion efficiency. Therefore, this paper chooses particle-particle optimization algorithm to solve the reverse logistics model in the e-commerce environment.

3.4.2. Improved Particle Motion Equation. From the perspective of social psychology, the ability of individuals to learn their own successful behavior is represented by learning factor C_1, which is also known as the cognitive factor, and C_2 is the social factor, which represents the ability to learn socially successful behavior. All areas centered on P_{gt} and P_{lt} can be searched by C_1 and C_2. In this paper, the search effect is again affected by the optimal value pct of each generation in each iteration. C_3 is defined as the time factor, which indicates the ability to learn the successful behavior of this iteration. The realization of this method mainly lies in the further improvement of the particle motion equation and the redefinition of an optimal position pct of the current generation of particles, which can make the particles not only close to the individual optimization and global optimization but also close to the optimal value of the current generation. In view of the particularity of DPSO, the subsection calculation method will achieve better results, because the effects on the dimensional data in the position are mutual [18].

4. Experiment and Analysis

4.1. Particle Swarm Optimization Process. The mathematical expression of the PSO algorithm is as follows: Assume that the dimension of the population center is d, and the size of the particle is n. The position and velocity of the ith particle are represented by the vectors $X_i = (x_{i1}, x_{i2}, \cdots, x_{id})$ and $V_i = (v_{i1}, v_{i2}, \cdots, v_{id})$; in each iteration, the particle follows two positive self-modifying solutions, one is the individual value of the particle, and the other is the global mass value observed by the entire population. The particle updates its speed and new position according to the following formula, as shown in

$$V_{id}(t+1) = w * V_{id}(t) + C_1 *_{r_1} * \left(P_{id(t)} - X_{id(t)}\right) + C_2 * r_2 * \left(P_{gd(t)} - X_{id(t)}\right), \tag{1}$$

$$X_{id}(t+1) = X_{id}(t) + V_{id}(t+1), \tag{2}$$

where $1 \le i \le N$ and $1 \le d \le D$, where C_1 and C_2 are positive learning factors, r_1 and r_2 are random numbers evenly distributed between 0 and 1, and W is called inertia weight. The initial position and velocity of the particle swarm are generated randomly and then iterate according to common (1) and (2) until a satisfactory solution is found. The flow of the PSO algorithm is shown in Figure 2.

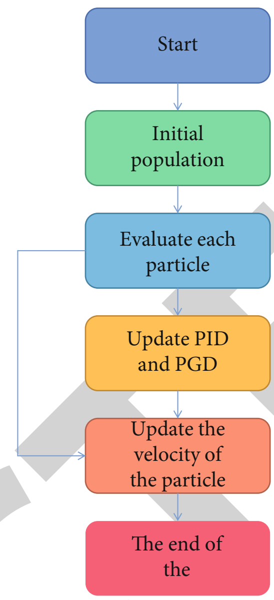


Figure 2: Flow chart of particle swarm optimization algorithm.

4.1.1. Standard Particle Swarm Optimization Algorithm. The particle swarm optimization (PSO) algorithm is an iterative-based optimization tool. It has the advantages of simple operation, good durability, and fast convergence speed and can be used in engineering practice. Let the search space be D-dimensional, and the total number of particles is n. The position of the ith particle is represented as a vector $X_1 = (X_{i1}, X_{i2}, \cdots, X_{iD})$, and the current optimal position of the ith particle is $P_i = (P_{i1}, P_{i2}, \cdots, P_{iD})$. The optimal particle position of all particles is $P_g = (P_{g1}, P_{g2}, \cdots, P_{gD})$, and the rate of change (velocity) of the ith particle position is the vector $V_i = (v_{i1}, v_{i2}, \cdots, v_{iD})$. The position of each particle is changed according to

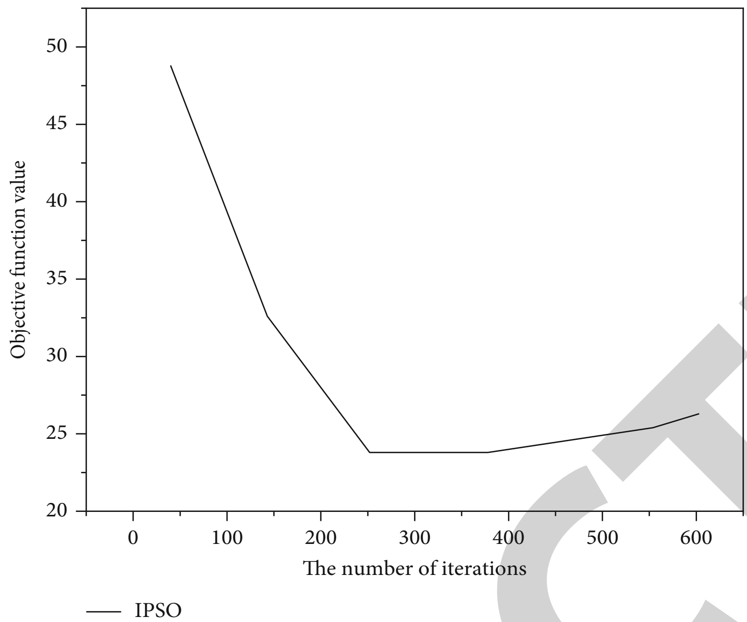
$$V_{id}(t+1) = \omega \times V_{id}(t) + c_1 \times \text{rand}\ () \times [p_{id}(t) - x_{id}(t)] + c_2 \times \text{rand}\ () \times \left[p_{gd}(t) - x_{id}(t)\right]$$
$$x_{id}(t+1) = x_{id}(t) + v_{id}(t+1), 1 \le i \le n, 1 \le d \le D \tag{3}$$

Among them, c_1 and c_2 are normal numbers, which are called acceleration constants; rand () is a random number between $[0, 1]$; and ω is the inertia weight.

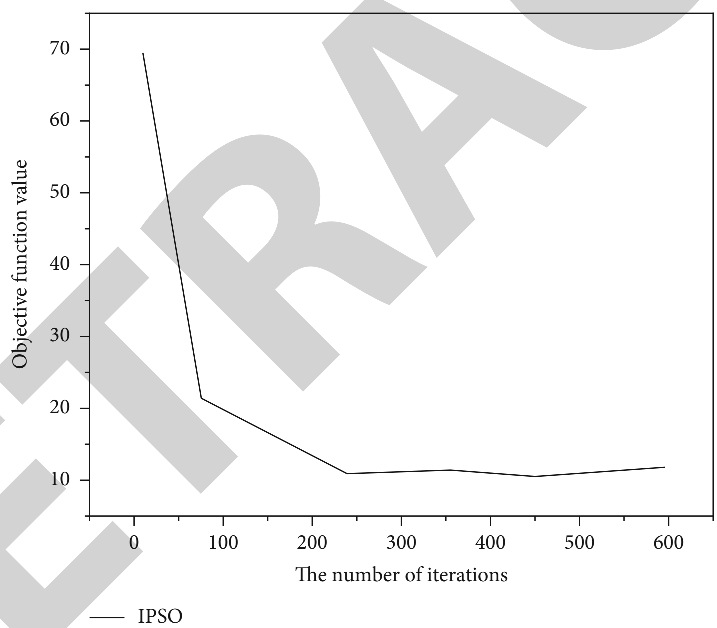
4.2. Improvement of Particle Swarm Optimization Algorithm. In standard particle swarm optimization algorithms, it is easy to prematurely converge to local cloud values due to the lack of diversity of particle positions in the next stage of exploration. Experiments show that it can be assumed that large C_1 and small C_2 were used in the preliminary investigation, so that the material is more easily separated into the study area with less interference. Intersects with the "socially conscious part" thus produce a wide variety of products. As the number of iterations increases, C_1 decreases linearly and C_2 increases linearly. With the increase in the number of iterations, C_1 decreases and C_2 increases, which strengthens the convergence ability of the global optimization of particles [19], as shown in

$$C_1 = C_{1s} + \frac{k(C_{1e} - C_{1s})}{k_{\max}},$$
$$C_2 = C_{2s} + \frac{k(C_{2e} - C_{2s})}{k_{\max}}, \tag{4}$$

where C_{1e} and C_{2e} are the final values of acceleration factors C_1 and C_2, C_{1s} and C_{2S} are the initial values of acceleration



(a) Convergence curve of sphere function



(b) Rosenbrock function convergence curve

Figure 3: Performance comparison of PSO algorithm before and after improvement.

Table 1: Particle coding.

Receiving point	1	2	…	N
Receipt number a_i	a_{i1}	a_{i2}	…	a_{in}
Formal order b_i	b_{i1}	b_{i2}	…	b_{in}

factors C_1 and C_2, K is the current number of iterations, and k_{max} is the maximum number of iterations.

In order to test that the performance of the IPSO algorithm is better than the PSO algorithm, two common benchmark functions are selected for comparison. The function form is as follows.

The sphere function is shown in

$$f(x) = \sum_{i=1}^{n} x_i^2. \tag{5}$$

Rosenbrock function is shown in

$$f(x) = \sum_{i=1}^{n} \left(x_i^2 - 10\cos\left(2\pi x_i\right) + 10\right). \tag{6}$$

Table 2: Required distribution volume of each receiving point.

Receiving point	Distribution volume	Receiving point	Distribution volume
1	11	5	12
2	17	6	6
3	7	7	9
4	5	8	12

Table 3: Distribution expenses of each receiving point.

Receiving point	Delivery cost (yuan)	Receiving point	Delivery cost (yuan)
1	98	6	103
2	56	7	98
3	46	8	75
4	83	9	54
5	56	10	53

For each test operation, set the center length to 20, the number of objects to 30, and the maximum number of iterations to 600. Figures 3(a) and 3(b) show the convergence curves of the PSO algorithm and the IPSO algorithm. Comparing the two functional tests in Figures 3(a) and 3(b), the IPSO algorithm outperforms the PSO algorithm in terms of speed dependence. The comparison results show that the IPSO algorithm can accelerate and solve the weakness of the PSO algorithm in local optimization. The comparison results determine the performance of the improved PSO algorithm.

4.2.1. Particle Coding Method. In the application of the particle swarm optimization algorithm, the coding method of particles is very important, which corresponds to the problem required to be solved. In this paper, the particle position is composed of three parts: receiving point, logistics distribution vehicle, and driving route. A three-row table is used to represent the position of each particle. The particle code is shown in Table 1 [20].

4.2.2. Particle Decoding Method

(1) For the element in the second row of particles α_{ij} rounding int (α_{ij}), the vehicle K assigned to point J can be obtained

(2) The driving path of vehicle k is determined according to the size order of the element b_{ij} of the third vector b_j of the matrix; that is, first find the point J where the distribution is completed by vehicle k and then sort from small to large according to the size of b_{ij} corresponding to j to determine the driving path of vehicle k [21, 22]

4.3. Simulation and Experiment. In order to test the solution performance of logistics cycle picking information of the IPSO algorithm, the simulation experiment is carried out by using VC++6.0 programming in the simulation environment of P42 core, 2.6 GHz CPU, 4 GB memory, and Windows XP operating system. The number of particles in the IPSO algorithm is 20, $\omega_{\max} = 5, \omega_{\max} = 1$. The simulation object is 1 distribution center, 12 receiving points, and 5 vehicles, the maximum load capacity of each vehicle is 20, the distribution volume required by each receiving point and the cost of each point are shown in Tables 2 and 3, and the minimum cost of the optimal scheduling scheme for the logistics distribution vehicle scheduling is 985 yuan [23, 24].

5. Conclusion

This chapter mainly discusses the principle of the particle swarm optimization algorithm. Through the analysis of gravitational inertia, it is shown that it is necessary to maintain large gravitational inertia in the initial stage to make the world a better place. At wood time, by reducing the inertia faster, we can improve the local optimization ability and rotation speed. On this basis, an improved particle swarm optimization algorithm based on inertial gravity nonlinear reduction is proposed. By studying and comparing different algorithms for solving nonlinear integer programming problems, the reasons and advantages of choosing particle-particle optimization algorithms are presented. It provides a basis for developing particle-by-particle optimization algorithms to solve inverse logical models in logical scenarios. Particle swarm optimization (PSO) takes the integration of birds as the optimization goal and generally simulates the flight and foraging behavior of birds. An improved particle swarm optimization algorithm is proposed to solve the upper model and lower model of the bilevel programming model, respectively. Simulation examples show the feasibility and effectiveness of this method.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The author declares that he has no conflicts of interests.

Acknowledgments

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