OPTIMIZATION OF INTELLIGENT LOGISTICS DISTRIBUTION ROUTE OF INTEGRATED LOADING AND UNLOADING BASED ON IMPROVED PARTICLE SWARM OPTIMIZATION

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ABSTRACT: Logistics distribution as a key component in the Intelligent Logistics System (ILS) determines the distribution efficiency and costs in the industry. It is more significant to schedule a reasonable route to improve distribution efficiency, reduce logistics cost and increase market competitiveness of enterprises. This paper aims to build a mathematical model for optimizing the routes of loading and unloading integrated logistics distribution vehicles, where the PSO integrates the immune algorithm to solve the model based on the improved PSO. The results from the simulation test show that the route optimization method based on the improved PSO is available for the intelligent logistics distribution vehicles of this type. After the test, it is found by the comparison that this method has a higher stability, reliability and efficiency than the other two algorithms. With this algorithm, the reasonable schedule is performed on distribution routes. It indeed has an important practical implication for improving the transportation efficiency, reducing the service cost and stimulating the development of logistics industry.

KEYWORDS: Improved Particle Swarm Optimization; Loading and Unloading Integration; Path Optimization; Intelligent Logistics

1 INTRODUCTION

Along with the development of the Chinese economy, the scale of e-commerce (Stylianou et al., 2003) has been expanding, and people's consumption has gradually transformed from offline (Sun & Li, 2012) to online models, and the distribution model from the mass production to low-volume production but many batches (Lin & Ho, 2009), which have presented significant challenges to the traditional operation model in logistics industry (Hong & Chin, 2007). In addition, with the boom of the traffic industry, the logistics distribution cost is also increasing, so causes a huge impact on the traditional logistics industry (Acar, 2012). Then the intelligent logistics (Zhou & Liu, 2002; Adamski, 2011) emerges. Intelligent Logistics (Eckhardt & Rantala, 2012; Hou et al., 2019) is a cross-industry and cross-cutting complex industry with high informatization (Lai et al., 2005), intelligence and networking. Till now, the current application has already spread to medicine, food and e-commerce, cold chain logistics, chain sales, military preparedness and many other industries.

According to the statistics, China's distribution cost (Langella & Zanoni, 2011) accounts for about 60% of the total in the logistics industry. In the intelligent logistics operation process, the logistics distribution chain not only determines the distribution efficiency but also impacts the logistics cost. As a key component in the ILS, a reasonable distribution route is important for improving the service quality and distribution efficiency, reducing the logistics costs, and increasing the market competitiveness of enterprises. In the context that the current logistics industry has seen a rapid development, the study of how to optimize the distribution routes is an objective demand for economic development (Desrochers et al., 1992; Laporte, 1992), since it will stimulate the economy in a positive feedback way. However, the distribution vehicle route optimization (Anderson et al., 2004) is a complex problem that involves operations research, combinatorial optimization, and graph theory disciplines, so that it is difficult to establish a model for it.

Based on the improved PSO algorithm, this paper takes the route optimization in logistics distribution as the study object to build a model for optimizing the intelligent logistics distribution routes of integrated loading and unloading, by which the distribution vehicles and transport routes are arranged in a reasonable manner. It is important
to improve the transportation efficiency and service quality, strengthen the industry competitiveness, and reduce the business costs.

2 INTELLIGENT LOGISTICS

2.1 Intelligent logistics

Logistics refers to a series of systematic activities launched in pursuit of high value-added, including customs clearance, transportation, warehousing and distribution. Intelligent Logistics System (ILS) is meant to imitate human thinking, learning and deduction in the fields of packaging processing, transportation and distribution, warehouse management, etc., based on the intelligent transportation system (Wang, 2010). As a modern logistics service system, it can address certain problems. The rapid rise of intelligent logistics is attributed to the fact that the automated ILS helps to improve the global efficiency and service level of the logistics industry, reduce the service costs and the waste of social and natural resources, so as to drive the economy to develop forward.

Compared with the developed countries, China's intelligent logistics is still in its infancy. Although it has made tremendous progress in a short time, it still faces many challenges, mainly reflected as follows:

(1) The relevant technologies for intelligent logistics are not advanced enough, and its supporting system is not perfect;
(2) The integration between transport system and logistics platform is not tight enough;
(3) The logistics company's business philosophy is relatively backward, the investments are less in talents and equipment, the efficiency of logistics operations is relatively low, and there is a serious depletion.

2.2 Optimization problem of intelligent logistics routes

Vehicle Routing Problem (VRP) refers to how to reasonably arrange the routes and quantity of the distribution vehicles under certain constraints in order to deliver a lot of goods from the supplier or distribution centers to several customer nodes. It should adapt to the optimization goals such as shortest routes or minimum cost. The distribution process is shown in Fig 2.

The distribution center can choose a distribution vehicle to complete the tasks, or several distribution vehicles for simultaneous delivery to fulfill the tasks. The schematic diagram of the distribution route is shown in Fig 3.

2.3 Types of intelligent logistics route optimization problems

There are 6 elements that make up the route optimization problem are shown in Fig 4, including road network, vehicles, customer, distribution centers, objective functions and constraints, each of which has different features and types, for example, the customer contains distribution outlets, warehouses, etc., and whether there is any
requirement for the delivery time (Bräysy & Gendreau, 2005), etc.; the objective function also includes multiple and single ones.

Therefore, in the practical logistics distribution process, the key elements of these route optimization problems will have different forms of combinations. The following lists several common types of optimization problems about intelligent logistics distribution routes, as shown in Table (1) below.

### Table 1. Types of Logistics Distribution Route Optimization

<table>
<thead>
<tr>
<th>Criteria for the Classification</th>
<th>Type of Division</th>
</tr>
</thead>
<tbody>
<tr>
<td>Delivery Center</td>
<td>Single distribution center; Multi- distribution center</td>
</tr>
<tr>
<td>Time Window Limit</td>
<td>Customer does not require delivery time; Customer has requirements for delivery time; Mixed time window problem</td>
</tr>
<tr>
<td>Travel Limit</td>
<td>Different vehicle mileage limits; All vehicle history limits the same problem; Unrestricted problem</td>
</tr>
<tr>
<td>Vehicle Operation Form</td>
<td>Only loaded; Discharge only; Loading and unloading integration</td>
</tr>
<tr>
<td>Optimization Goal</td>
<td>Good service quality; Low line cost; Less vehicle usage</td>
</tr>
</tbody>
</table>

3 ESTABLISHMENT OF ROUTE OPTIMIZATION MODEL FOR LOADING AND UNLOADING INTEGRATION

3.1 Description of loading and unloading integrated vehicle route optimization problem

In order to improve the efficiency of the distribution system, the distribution route is determined by considering the delivery and pickup of the modern logistics system while building the model. In the practical delivery process, there will be an indefinite number of delivery and receipt points. The distribution vehicle will be unloaded at the delivery point, loaded at the receipt point, but the two will take place at the demand point. This is the problem about the loading and unloading integrated intelligent logistics distribution widely applied now.

The problem can be described such that: a company has $M$ distribution centers which serve $N$ customer points with loading or unloading businesses. The number of distribution vehicles sent by the distribution center $m$ is $K_m$, and the loading and unloading volumes at $i$ customer points have not exceeded the rated cargo capacity $Q_{mk}$. How to arrange a reasonable driving route to achieve less expenses or the minimal total journey.

3.2 Model assumption and establishment

Before building a mathematical model, the following constraints must be met, that is, the model makes the assumptions as follows:

1. The vehicles in the distribution center are exactly identical. Each distribution vehicle departs from the initial point and returns to the original distribution center after the shipping is complete;
2. Each distribution vehicle only takes one route and can serve multiple customer points on this route;
3. The cargo dead weight of each distribution vehicle on the whole distribution route shall not exceed the approved load capacity;
4. Each customer point can only accept the loading and unloading services of a distribution vehicle, and the loading and unloading volumes are constant;
5. Delivery services are limited by the time window of the customer points.

According to the above description and constraints, the objective function of the intelligent logistics distribution route optimization problem for the multi-distribution center is the minimal total distance. The mathematical model is shown in the following formula (1):

$$\min Y = \sum_{m=1}^{M} \sum_{k=1}^{K_m} \left\{ \sum_{i=1}^{N} \left[ d_{r_{mk(i-1)}} r_{mk} + d_{r_{mknk0}} \right] \right\}$$

where, $M$ represents the number of distribution centers; $N$ represents the number of customer points; $K$ represents the number of delivery vehicles; $d$ represents the transport distance from one customer point to another.

In addition, the constraints are true as shown below:

$$\sum_{i=1}^{N} v_{mr_{mk}} \leq Q_{mk}$$

(2)
\[ \sum_{i=1}^{n_{mk}} d_{mk(i-1)}r_{mk} + d_{mk(n_{mk})}r_{mk0} \varphi(n_{mk}) \leq D_{mk} \quad (3) \]

\[ 0 \leq n_{mk} \leq N_m \quad (4) \]

\[ \sum_{k=1}^{K_m} n_{mk} = N_m \quad (5) \]

\[ \sum_{m=1}^{M} N_m = N \quad (6) \]

\[ R_{mk} = \{ r_{mk(1)}r_{mk(2)} \in \{1,2,\ldots,n\}, i = 1,2,\ldots,n_{mk} \} \quad (7) \]

\[ R_{mk1} \cap R_{mk2} \neq \emptyset, \forall m \neq m_k \quad (8) \]

\[ \varphi(n_{mk}) = \begin{cases} 1, & n_{mk} \geq 1 \\ 0, & \text{Others} \end{cases} \quad (9) \]

where \( Q_{mk} \) represents the load of the delivery vehicle; \( D_{mk} \) represents the longest travel distance for the vehicle to complete a delivery; \( R_{mk} \) represents the customer point on the delivery route; \( \varphi(n_{mk}) \) represents whether the distribution vehicle participates in the delivery task.

### 3.3 Improved PSO

1. **PSO**

Particle Swarm Optimization (PSO) is an intelligent computation method based on the abstraction and evolution of the foraging behaviors of the bird population. It seeks the global optimum of the objective problem. The principle of this algorithm is simple and easy to implement, but the global search capacity is relatively poor. It is easy to fall into the local optimum, and has a poor solution accuracy.

2. **Immune algorithm**

Immune algorithm is one that simulates the immune defense mechanism in the organisms. It applies the biological reactions such as immune memory, immune regulation and antigen recognition in the immune system to get the optimal solution in practical projects. The immune algorithm has immunological memory capacity and regulation mechanism and ensures the diversity of antibodies, thus avoiding the occurrence of premature phenomenon, but it has a low solution efficiency.

3. **Design of improved PSO**

This paper integrates the immune algorithm and the PSO, as shown in Fig 5. The immune regulation mechanism of the immune algorithm can help fill the gaps of the PSO such as premature convergence, easy to fall into the local solution, and low solution accuracy, so that the improved PSO can quickly find the globally optimal solution. The improved PSO inherits the features of both immune algorithm, such as the global convergence, immune memory mechanism, and general algorithms, such as simple implementation and positive feedback, which can improve the solution accuracy and convergence speed of the algorithm.

In the improved PSO, the concept of "antibody" in the immune algorithm is identical to the "particle" in the PSO, collectively referred to as "particle" here. By adjusting the antibody concentration, it is possible to ensure the diversity of the particles, and that the particles with high fitness can be reserved. The process of the improved PSO is shown in Fig 6.

### 4 SIMULATION TEST

#### 4.1 Test environment

In order to test the model effectiveness, this paper takes a logistics company as an example, where there are two logistics centers L1 (30, 70)
and L2 (70, 55) in an area. 2 distribution vehicles with a deadweight cargo capacity of 10 t. are equipped for providing 15 customer points with loading and unloading services. The maximum distance that the distribution vehicle can drive for completing a delivery task is 150km, and the maximum speed cannot exceed 80km/h. The loading and unloading information, location information, service time and time window at each customer point are shown in Table (2) below.

<table>
<thead>
<tr>
<th>Customer Point Number</th>
<th>Position Coordinates</th>
<th>Unloading Volume (t)</th>
<th>Loading Volume (t)</th>
<th>Service Hours (h)</th>
<th>Delivery Period (h)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>(20, 53)</td>
<td>3</td>
<td>2</td>
<td>1</td>
<td>[3, 5]</td>
</tr>
<tr>
<td>2</td>
<td>(30, 45)</td>
<td>2</td>
<td>2</td>
<td>0.5</td>
<td>[4, 6]</td>
</tr>
<tr>
<td>3</td>
<td>(50, 75)</td>
<td>2</td>
<td>0</td>
<td>0.5</td>
<td>[1, 5]</td>
</tr>
<tr>
<td>4</td>
<td>(68, 70)</td>
<td>4</td>
<td>3</td>
<td>1.5</td>
<td>[2, 7]</td>
</tr>
<tr>
<td>5</td>
<td>(60, 33)</td>
<td>5</td>
<td>3</td>
<td>2</td>
<td>[3, 5]</td>
</tr>
<tr>
<td>6</td>
<td>(75, 79)</td>
<td>4</td>
<td>2</td>
<td>2</td>
<td>[1, 3]</td>
</tr>
<tr>
<td>7</td>
<td>(32, 88)</td>
<td>3</td>
<td>0</td>
<td>1</td>
<td>[1, 4]</td>
</tr>
<tr>
<td>8</td>
<td>(60, 66)</td>
<td>2</td>
<td>1</td>
<td>1</td>
<td>[4, 7]</td>
</tr>
<tr>
<td>9</td>
<td>(21, 18)</td>
<td>1</td>
<td>2</td>
<td>1.5</td>
<td>[0.5, 3]</td>
</tr>
<tr>
<td>10</td>
<td>(14, 62)</td>
<td>3</td>
<td>2</td>
<td>2</td>
<td>[2, 5]</td>
</tr>
<tr>
<td>11</td>
<td>(64, 33)</td>
<td>2</td>
<td>0</td>
<td>1</td>
<td>[2, 5]</td>
</tr>
<tr>
<td>12</td>
<td>(55, 98)</td>
<td>2</td>
<td>1</td>
<td>1.5</td>
<td>[2, 5]</td>
</tr>
<tr>
<td>13</td>
<td>(87, 42)</td>
<td>4</td>
<td>3</td>
<td>2</td>
<td>[1, 4]</td>
</tr>
<tr>
<td>14</td>
<td>(38, 78)</td>
<td>1</td>
<td>0</td>
<td>0.5</td>
<td>[2, 4]</td>
</tr>
<tr>
<td>15</td>
<td>(97, 30)</td>
<td>5</td>
<td>2</td>
<td>2.5</td>
<td>[4, 6]</td>
</tr>
</tbody>
</table>

4.2 Test

For the sake of simple intuition, this paper uses the natural numbers to encode the customer points, that is, 1, 2, ..., 15; the codes of the distribution centers L1 and L2 are 21 and 22, respectively. The mathematical model built in 3.2 is applied to the distribution case of loading and unloading integrated intelligent logistics in 4.1, then programed in C to realize the design of the improved PSO, and solve the problem against the instance. Simultaneously, in order to test the effectiveness and reliability of the improved PSO, both the immune algorithm and the PSO are adopted for a comparison in the test. It is assumed that the size of particle swarm, N, is set to 30; the number of iterations is 100; the initial inertia weight is 1, and finally decreases to 0; the affinity threshold between antibodies is 0.5; the affinity threshold between antibody and antigen is 0.7.

4.3 Test results and analysis

After the improved PSO is used to solve the problem in the example, the optimal route program is shown in Fig 7.

Where, Route 1: 21-10-1-9-2-21,84.32km;
Route 2: 21-7-12-3-14-21,95.44km;
Route 3: 22-8-4-6-22,58.72km;
Route 4: 22-5-11-15-13-22,80.66km.

The total route is 319.14km, and the average operation time of the improved PSO is 4.28s. The total distances of the optimized route available by the immune algorithm and the general PSO are 319.04km and 398.56km, respectively. 8 test results are taken to compare three algorithms for stability and effectiveness, as shown in Fig 8 below. From the test results, the improved PSO reaches the optimal route in 5 out of 8 tests, and the immune algorithm does optimal route 3 times. The convergence probabilities are 62.5% and 37.5%, respectively. The PSO can find quite different solutions, whose reliability and stability cannot be guaranteed.
Fig 8. Experimental Results of Three Algorithms

It is observed from the above figure that the stability of the optimal route solution of the immune algorithm is also better, so that it is impossible to judge the difference between the immune algorithm and the improved PSO. The 20th generation of evolved results in a test are chosen to observe its convergence, in order to judge the effectiveness and reliability of the improved PSO. The iterative results are shown in Fig 9.

Fig 9. The Convergence Analysis of Three Algorithms

It is found from the above figure that the three algorithms have finished basic convergence. The improved PSO achieves the optimal route solution in the 8th iteration, and remains stable, with fast convergence and high accuracy. The immune algorithm reaches the optimal solution in the 10th generation, but has relatively slow convergence speed and low stability; the PSO falls into the local optimum and fails to obtain the optimal solution, and its convergence speed is slow.

It is known from the above test results that the improved PSO for intelligent logistics distribution route optimization can effectively avoid premature, has strong global optimization capacity. Beyond that, it also has better convergence speed and solution accuracy than the immune algorithms and the general PSO.

5 CONCLUSION

Based on the improved PSO, this paper discusses the intelligent logistics distribution route optimization problem of loading and unloading integration, and comes to the following conclusions:

(1) The PSO integrates the immune algorithm for the improvement, filling the gaps of the PSO that is prone to the premature and local optimum. This improved algorithm realizes simple, global optimization and convergence, etc., so as to improve the algorithm speed and accuracy.

(2) In this paper, the improved PSO algorithm is used to solve the loading and unloading integrated logistics distribution model. It is proved by the simulation test that this algorithm is effective and reliable. In addition, after the comparison with test results of immune algorithm and PSO, it is showed that the improved PSO has better stability and efficiency than other algorithms.

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7 REFERENCES