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Research on Distribution Management Information Platform of Chemical Products based on GIS

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With the development of chemical industry and the continuous improvement of infrastructure, logistics is becoming more and more important in the national economy. The problem of vehicle routing has been widely used in transportation, logistics, vehicles scheduling and industrial production. A reasonable distribution route can improve the efficiency of logistics distribution and reduce the cost. Because of its particularity, the chemical products have higher requirements for the vehicle flow, road condition and total mileage of the delivery route. In this paper, a dynamic particle swarm optimization algorithm is proposed by introducing the dynamic inertia weight coefficient, which balances the global search ability and the local search ability. Firstly, the theory of traditional particle swarm optimization (PSO) is introduced. Secondly, by optimizing the traditional weighting coefficients, we propose a dynamic particle swarm optimization algorithm, which improves the convergence speed effectively. Thirdly, based on the spatial geographic information technology (GIS), the distribution management information platform of chemical products is designed in detail. Finally, the path optimization algorithm proposed in this paper is simulated and verified. The results show that the improved algorithm can quickly and effectively determine the delivery route, which has great application value.

1. Introduction

The distribution of chemical products is not only the simple transportation of chemical products, but also needs to be considered comprehensively from the aspects of safety, timeliness and economy. The efficient delivery process of chemical products has become a cross fusion industry integrating internet of things, navigation, positioning, intelligent transportation and other new technologies (Zhou, 2010).

As a key problem in the field of logistics and distribution, vehicle scheduling management has been a research hotspot in the field of logistics, and many excellent path scale models and algorithms have been put proposed. Li et al., (1998) sets the evaluation function on the time window constraint, and applies the nearest distance heuristic algorithm to solve the simple vehicle routing problem. Liu et al., (2004) gets a good result by using simulated annealing algorithm on vehicle routing problem with stochastic demand of two models. Yuan et al., (2003) uses neural network algorithm to solve vehicle routing problem, which is proved to be a good method. Bernd et al., (1999) designs a special ant colony transfer strategy for vehicle routing problem, and optimizes the route with 2-Opt algorithm. Gambardella et al., (1999) applies the ant colony algorithm to the vehicle routing problem with time windows, and creatively designs two populations, which are used to optimize the total route length and the total vehicle number.

The spatial geographic information technology is an important means in the process of distribution management informatization. Since the management platform based on GIS is mainly input and output in the form of digital map, the operation is intuitive and easy to understand, which can be easily accepted by the users. Many excellent management tools have introduced GIS technology. Li et al., (2010) combines the intelligent optimization algorithm with the GIS spatial analysis technology, which can provide some decision reference for the spatial optimization decision problem. Mi et al., (2015) simulates the optimal layout of land use in computer environment by combining GIS with intelligent optimization algorithm.

In this paper, a dynamic particle swarm optimization algorithm is proposed by introducing the dynamic inertia weight coefficient, which balances the global search ability and the local search ability. Firstly, the theory of traditional particle swarm optimization (PSO) is introduced. Secondly, by optimizing the traditional weighting

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coefficients, we propose a dynamic particle swarm optimization algorithm, which improves the convergence speed effectively. Thirdly, based on the spatial geographic information technology (GIS), the distribution management information platform of chemical products is designed in detail. Finally, the path optimization algorithm proposed in this paper is simulated and verified. The results show that the improved algorithm can quickly and effectively determine the delivery route, which has great application value.

2. Basic particle swarm optimization

Particle swarm optimization (PSO) is a swarm intelligence algorithm that simulates the flight of a flock of birds. In the algorithm, each particle is considered as a feasible solution of the problem, and the optimal solution of the problem is finally found by tracing the current and the historical particles. In each iteration of the particle swarm, the particle updates itself by tracking individual extremum and global extremum. The flow chart of particle swarm optimization algorithm is as follows.

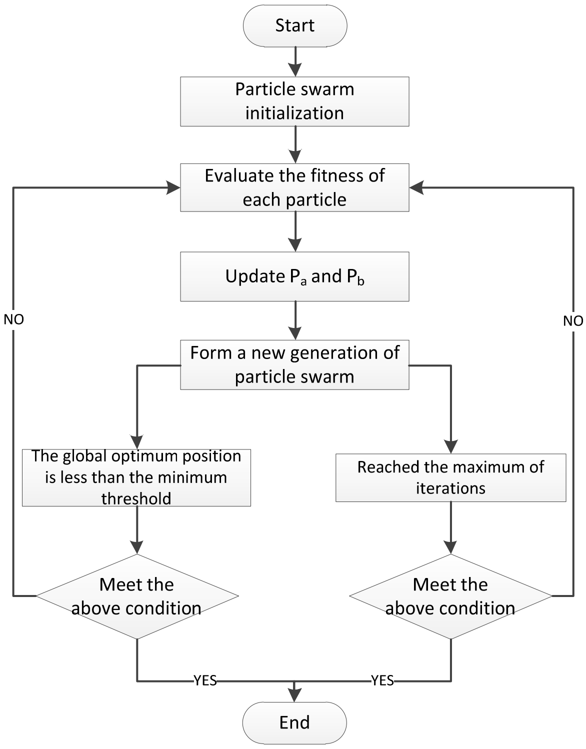

Figure 1: Flow chart of particle swarm optimization algorithm

We assume that in a *K* dimensional space there is a set *P*, which consisting of *m* particles.

$$P = \begin{pmatrix} p_{11} & \cdots p_{1i} \cdots & p_{1m} \\ \vdots & & \vdots \\ p_{j1} & \ddots & p_{jm} \\ \vdots & & \vdots \\ p_{k1} & \cdots p_{ki} \cdots & p_{km} \end{pmatrix} \tag{1}$$

The position of the particle *i* in the *K* dimensional space can be expressed as follows.

$$P_i = \begin{bmatrix} p_{i0} \\ p_{i1} \\ p_{i2} \\ \vdots \\ p_{ik} \end{bmatrix} \tag{2}$$

By introducing P_i into the objective function, the fitness of the particle can be obtained. We define that speed of the particle at moment *t* is as follows.

$$V_i = \begin{bmatrix} v_{i0} \\ v_{i1} \\ v_{i2} \\ \vdots \\ v_{ik} \end{bmatrix} \tag{3}$$

When the particle swarm is iterated every time, the speed of the particle will be updated by the following formula.

$$V_{ik}^{g+1} = V_{ik}^{g} + \sigma_1 r_1 (P_{ak}^{g} - P_{ik}^{g}) + \sigma_2 r_2 (P_{bk}^{g} - P_{ik}^{g}) \tag{4}$$

In the formula, σ_1 and σ_2 are the acceleration coefficients which are used for initialization. *g* is the evolutionary generation of the particle swarm. Besides, r_1 and r_2 are random coefficients. In order to better coordinate the global and local optimization ability of particle swarm, the inertia weighting factor w is introduced.

$$V_{ik}^{g+1} = w \cdot V_{ik}^{g} + \sigma_1 r_1 (P_{ak}^{g} - P_{ik}^{g}) + \sigma_2 r_2 (P_{bk}^{g} - P_{ik}^{g}) \tag{5}$$

When the particle swarm is iterated every time, the position of particle will be updated by the following formula.

$$P_{ik}^{g+1} = P_{ik}^{g} + V_{ik}^{g+1} \tag{6}$$

3. Improved dynamic particle swarm optimization

The inertia weight *w* of the standard particle swarm algorithm is a constant, which is not flexible enough to balance the relationship between global search ability and local search ability of particle swarm. In order to solve the deficiency of particle swarm optimization in path optimization process, we improve the inertia weight *w* of the basic particle swarm optimization according to the characteristics of multi-objective constrained optimization in the process of logistics distribution. So, a dynamic inertia weight consistent which is consistent with nonlinear variations is proposed as follows.

$$w = w_0 + (w_1 - w_0) \cdot \frac{1}{e^{\frac{n}{N_{\max} - n}}} \tag{7}$$

Where, *n* is the number of current iteration, and N_{max} is the maximum number of iteration. The new dynamic inertia weight coefficient not only keeps the particle diversity, but also prevents the emergence of the local optimum defect.
Assume that the distance between customer *i* and customer *j* is *d*(*i*, *j*), we can build the following model.

$$Rou = \sum_{i=1}^{V} \left(\sum_{j=1}^{T} d(r_v^{j-1}, r_v^{j}) + d(r_v^{T}, 0) \right) \cdot \mathrm{sgn}(T) \tag{8}$$

Where, r_v^j indicates that the order of customerin the vehicle distribution route is *j*, and T means the total number of customers to be delivered by vehicle *v*. If *T*=0, it means that the vehicle has no task of delivery, the parameter sgn(*T*) satisfies the following conditions.

$$\mathrm{sgn}(T) = \begin{cases} 1 & \mathrm{T} \geq 1 \\ 0 & \mathrm{T=0} \end{cases} \tag{9}$$

Thus, the constraint condition of route optimization is as follows.

$$\begin{cases} C_{v1} \cap C_{v2} = \phi \\ \sum_{j=1}^{T} d(r_v^{j-1}, r_v^{j}) + d(r_v^{T}, 0) \le L_V \\ \bigcup_{i=1}^{V} C_3 = C_1 \cup C_{v2} \cdots \cap \cup C_v = \{1, 2, 3 \cdots N\} \end{cases} \tag{10}$$

In the above formula, L_V represents the maximum distance which is travelled by the vehicle, and C_i represents the collection of customers which require vehicle v to delivery.
In order to ensure the convergence of the algorithm, we use the convergence factor ι as a parameter of the formula and so we can get the new update function.

$$V_{ik}^{g+1} = \gamma \cdot (w \cdot V_{ik}^{g} + \sigma_1 r_1 (P_{ak}^{g} - P_{ik}^{g}) + \sigma_2 r_2 (P_{bk}^{g} - P_{ik}^{g})) \tag{11}$$

We let $\theta = \sigma_1 + \sigma_2$, and the convergence factor γ can be expressed as follows.

$$\gamma = \frac{2}{|2 - \theta - \sqrt{\theta^2 - 4\theta}\,|} \tag{12}$$

According to the above formulas, we can get that the logistics distribution not only requires less delivery vehicles, but also requires the shortest delivery path. Therefore, the search of the optimal path is the most key link.

4. Application of GIS in distribution management of chemical products

As a technical means, GIS has unique advantages in processing and analyzing complex spatial data. Where, visualization and easy to operate are the biggest highlights. The distribution management platform of chemical products based on GIS is mainly composed of five layers, and they are presentation layer, control layer, model layer, data persistence layer and data layer. The system architecture of distribution management platform is as follows.

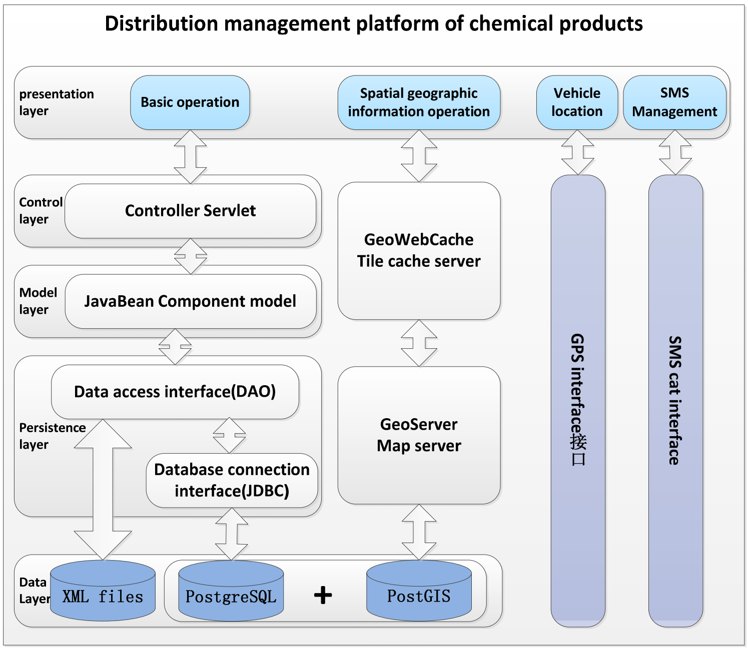

Figure 2: System architecture of distribution management platform

The presentation layer refers to the part that interacts with users, and in the mode of B/S, it means the browser. The presentation layer uses JSP, HTML, JavaScript, and other technologies to answer for the user's various operations and some data analysis. In addition, some map operations are done at the presentation layer.

The control layer mainly refers to the processing and forwarding of the user's request, and it also can feedback the analysis result of the system to the user. In the distribution management platform of chemical products, the main business of this layer is realized by Servlet.
The model layer encapsulates the data associated with the business logic as well as some methods of processing the data. In the management platform, we use JavaBean reusable components as model layer.
The data persistence layer, which is also called the data access layer, is responsible for the operation of data in storage devices, such as data addition, deletion, modification and query. In order to reduce the coupling and improve the cohesion, this layer is subdivided into data operation part and database connection part which realize the further separation of business operation and data access.
The Data layer is the part of data storage. In the management platform, it mainly refers to the database part, which is mainly responsible for storing data in the server storage device.
The development of cloud service technology has greatly reduced the investment of chemical manufacturers in server hardware facilities and administrators, which makes it easier for the management platform to become popular among chemical manufacturers.

5. Simulation experiment and analysis

For the optimization verification of two intelligent algorithms, this paper compares the improved particle swarm optimization algorithm with the standard particle swarm algorithm from the aspects of the optimal path and the convergence speed. The acceleration coefficient of standard particle swarm algorithm is set as follows.

$$\sigma_1 = \sigma_2 = 1.5 \tag{13}$$

And the inertia weight coefficient is set to 0.4.
A．Comparison of search paths in the same environment
Through the simulation results in figure 3, we can get that the path of the improved particle swarm optimization is{(0,0),(1,1),(2,3),(3,4),(4,5),(5,7),(6,7),(7,8),(8,10),(9,11),(10,12),(11,12),(12,12),(13,13),(14,14),(15,15)}.
The fitness value of global optimal path is 26. While the fitness value of the standard particle swarm optimization is 27 and set {(0,0),(1,1),(2,3),(3,4),(4,7),(5,7),(6,7),(7,7),(8,8),(9,8),(10,8),(11,8),(12,10),(13,13),(14,14), (15,15)} represents the path of the standard particle swarm algorithm. Although the standard particle swarm algorithm performs better in local path planning, the improved particle swarm algorithm performs better in global path.

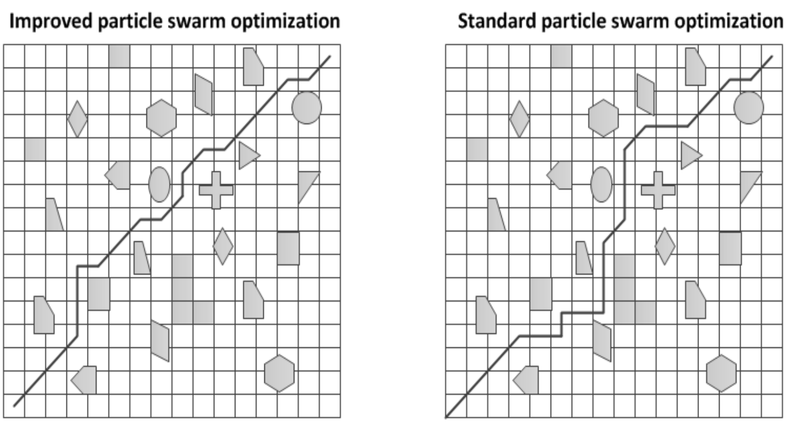

Figure 3: The comparison diagram of global optimal paths

B．Comparison of convergence rates in the same environment
Figure 4 shows the convergence process of the optimal solution generated by the improved particle swarm algorithm and the standard particle swarm algorithm. By comparison, it can be seen that the two algorithms can reach the local optimal solution quickly. However, as the number of iterations increases, the standard particle swarm algorithm does not jump out of the local optimum. Meanwhile, the improved particle swarm algorithm finds a better solution of 26 when the number of iterations reaches 190. Therefore, the improved particle swarm optimization algorithm is much better than the standard particle swarm algorithm in overcoming the local optimum.
Through simulation experiment, we can get that the improved dynamic particle swarm algorithm has faster search performance and better planning ability than the standard particle swarm optimization algorithm. What

is more, the new algorithm also performs well in terms of convergence speed. Corresponding to the particularity of chemical products in transportation process, the improved particle swarm optimization algorithm can help enterprises achieve safe and efficient delivery in the process of chemical product distribution.

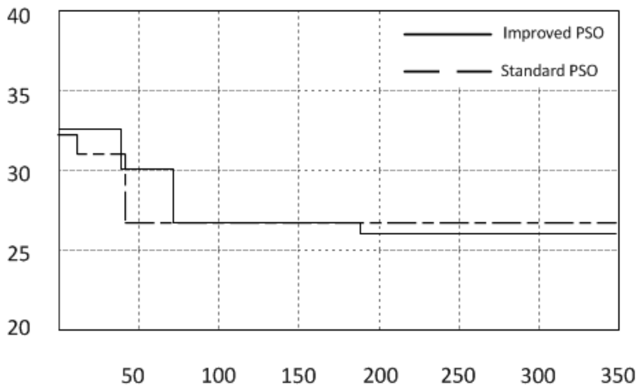

Figure 4. The contrast diagram of the convergence process

6. Conclusion

As a result of the introduction of GIS, the distribution management information platform of chemical products based not only realizes the real-time monitoring of chemical products logistics distribution, but also provides efficient path planning capabilities for transportation vehicles. In spite of this, this paper does not take into account the weather, altitude and other factors in the transportation of chemical products, which affects the accuracy of the algorithm to some extent. In the future, it is believed that better algorithms and models will be used in the distribution management of chemical products.

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