

# Vehicle Driving Network Routing Optimization Algorithm Based on Drosophila Algorithm

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**Keywords:** Vehicle routing; optimization; drosophila algorithm

**Abstract.** In order to discuss the vehicle routing problem, which is a combination optimization problem, we apply drosophila algorithm. First of all, we introduces the fundamental concepts of drosophila algorithm and describes the specific implementation steps. Secondly, we analyze vehicle routing problem and mathematical model and do a simulation experiment to explore the effect and performance of drosophila algorithm. The experimental results show that the improved drosophila algorithm, compared with the common drosophila algorithm, can improve the solution accuracy indeed, and it efficiently solves the vehicle routing problem. As a result, it can be concluded that, in order to effectively solve the typical combination optimization problem - vehicle routing problem, it is necessary to apply artificial intelligent method, which has rather good performance and it can improve the accuracy of algorithm.

## 1. Introduction

Logistics distribution path optimization problem, namely vehicle routing problem (VRP), is a combination optimization problem, and also a typical NP difficult problem. In 1959, two scientists Dantzing and Ramser abstracted the logistics and distribution activities on the basis of Travelling Salesman Problem (TSP), and proposed VRP problem for the first time. The problem can be described as [1]: vehicle starts from the distribution center, and under the condition of meeting certain constraints (vehicle capacity constraints, mileage limit, delivery time limit and so on), delivers the goods to each receiving point, and reaches a certain optimization target (the least vehicle used, the minimum mileage, the minimum cost, the minimum service, and delivered within the specified time and so on). According to the different classification bases, the VRP problem can be classified into several categories. According to the number of distribution centers, it can be divided into a single distribution center problem and a multi distribution center problem. While according to the distribution vehicle type, it can be divided into single vehicle problem (all vehicle capacity, load capacity, maximum mileage and so on are the same) and multiple vehicle models [2]. According to the classification of distribution types, it can be divided into the problem of pure delivery, the problem of pure goods taking and the mixing of delivering goods and picking up goods. According to the subsidiary relationship between distribution vehicle and distribution center, it can be divided into open vehicle problem (vehicle must return to distribution center after completion of distribution task) and closed vehicle problem (after completion of distribution task, vehicles do not have to return to distribution center).

In the paper, first of all, the fundamental concepts of drosophila algorithm are introduced and the specific implementation steps are described. The swarm intelligence algorithm is described briefly, and then the original drosophila algorithm is illustrated. Secondly, the vehicle routing problem and mathematical model are analyzed and a simulation experiment is done to explore the effect and performance of drosophila algorithm. The improved drosophila algorithm is adopted to conduct expression, modeling, and solution of vehicle routing problem. In addition, the proposed algorithm is applied to do an experiment for the two groups of data sets. And through the comparative analysis of experimental results, the feasibility and effectiveness of the algorithm is verified.

## 2. Introduction to Drosophila Algorithm

### 2.1 An Overview of Swarm Intelligence Algorithm

Swarm Intelligence (SI) refers to the collective behavior of distributed and self-organizing systems in the natural or artificial fields. The expression was first proposed by Gerardo Beni and Jing Wang in *Swarm Intelligence in Cellular Robotic Systems* the 1989, which is derived from the observation of collective cooperative behavior displayed by insect population in nature [3]. In a population, a single individual does not show intelligence, but the interaction and collaboration between them will show the intelligence of the group, such as ant colony's foraging behavior. During the process of finding food, ants secrete a kind of secretory thing called "information" on each path, and the more the pheromones secreted the closer to food. In the colony, ants will generally choose the path with the largest concentration of information. In this way, after a period of time, it will form a shortest path to from ant nest to food, and get most of the ants together on the path.

Group intelligent systems have the following characteristics compared with other optimization systems: The cooperative individuals in the group are independent of each other. The system does not have central control but has strong stability. All individuals in a group have the ability to change the environment. Individuals communicate information with each other through indirect communication and cooperate with each other so that groups can be expanded. The individuals need to follow simple rules in the group, and in this way, they can complete the simple task, and the behavior is single and easy to be realized [4]. The group has self-organization, and the individual's simple behavior can make the group have complex behavior through the interaction.

The swarm intelligence algorithm generally has two characteristics: extensibility and convergence. Extensibility refers to the search capability of the algorithm for the solution space, and convergence is the ability for the algorithm to get close to the optimal solution. However, these two characteristics are contradictory to each other, while the general swarm intelligence algorithm cannot well coordinate the two capacities. When the algorithm shows good extensibility, the convergence will be poor; on the other hand, when the algorithm exhibits good convergence, its extensibility is poor.

### 2.2 Drosophila Optimization Algorithm

Drosophila, though small in size and only 3 to 4 millimeters in length, is at the bottom of the food chain in nature. However, compared with other populations, drosophila has powerful perception ability, especially smell and vision. Its rich olfactory organs can smell a variety of smells that diffuse in the air, and they can even smell food sources 40 kilometers away [5]. When the drosophila was foraging, it firstly will use the strong smell ability, and rapidly fly to the area with the highest concentration of food smell. When getting close to the food source, they will use sharp vision, and get close to the optimal individual closest to the food population so that they can quickly find food.

According to the foraging behavior of drosophila group, Pan Wenchao, a Chinese scholar in Taiwan, proposed a new swarm intelligence optimization algorithm - drosophila optimization algorithm in 2011 [6]. Drosophila optimization algorithm is the abstract of strong sense of smell and visual search when the drosophila is foraging. Its basic principle includes two parts: the first one is olfactory random search. According to the food smell concentration, drosophila will judge the estimated range of food, and determine the random direction and length of flight, so as to get close to the food. The second one is visual localization. When approaching to the food source, other drosophila individuals in the population can use the keen vision to observe the location of the drosophila individual with the largest odor concentration in the population and reach the location of the best drosophila quickly.

Table 1 is a comparison of the optimization performance for the drosophila algorithm and the other 5 population intelligent algorithms. From this table, we can see that, compared with other swarm intelligence algorithms, such as particle swarm optimization, ant colony algorithm and fish swarm algorithm, drosophila algorithm has the advantages of small computation, simple implementation and high accuracy. Because of these advantages, drosophila algorithm has been widely applied in distribution network planning, distribution center location, mathematical function solving extremum, SVM parameter optimization and so on.

Table 1. Comparison of the optimization performance for the drosophila algorithm and the other 5 population intelligent algorithms

Algorithms	Computation	Complexity	Stability	Accuracy
Ant colony optimization (ACO)	Moderate	Complex	Stable	High
drosophila algorithm	Small	Simple	Unstable	High
Fish swarm algorithm (FSA)	Comparatively large	Complex	Stable	High
Immune algorithm (IA)	Rather large	Complex	Stable	High
Genetic algorithm (GA)	Comparatively large	Rather complex	Stable	Low
Particle swarm optimization (PSO)	Moderate	Simple	Unstable	Rather low

The specific implementation steps are shown as follows:

Step 1: initialization. Determine the group scale sizepop, the maximum iteration times maxiter and the group initial position (Xaxis, Yaxis).

Step 2: conduct random search according to smell. In accordance with the food smell concentration, drosophila determines the random direction and step length of flying. RandomValue represents the random flying step length, and then the search formula according to smell is shown as follows [7]:

$$\begin{aligned} X_i &= X_{axis} + RandomValue \\ Y_i &= Y_{axis} + RandomValue \end{aligned} \quad (1)$$

Step 3: calculate the smell concentration judgement value. The judgement value of food smell concentration is reciprocal of the distance from the drosophila individual to origin, shown as follows:

$$S_i = \frac{1}{\sqrt{X_i^2 + Y_i^2}} \quad (2)$$

Step 4: calculate the smell concentration (fitness function value). according to the smell concentration judgement value, we calculate the smell concentration:

$$Smell_i = Function(S_i) \quad (3)$$

Step 5: find the drosophila individual (the optimal individual) with the highest smell concentration in the current population. Among them, bestSmell refers to the smell concentration of the current optimal individual, and bestIndex is the number of the current optimal individual.

$$[bestSmell, bestindex] = \max(Smell) \quad (4)$$

Step 6: locate according to the vision. Record the location (X,Y) of current population optimal drosophila and the highest smell concentration bestSmell. Other individuals in the population flies to the optimal drosophila through the vision observation [8].

$$\begin{aligned} smellBest &= bestSmell \\ X_{axis} &= X(bestIndex) \\ Y_{axis} &= Y(bestIndex) \end{aligned} \quad (5)$$

Step 7: Find the optimal by iteration. When the current iteration times  $t < maxiter$ , repeat setp2 to step 5, and judge whether the current optimal smell concentration is superior to the last iteration. If it is, then implement step 6 [9]. When  $t = maxiter$ , the algorithm ends.

### 3 Solution of VRP Problem by Drosophila Optimization Algorithm

#### 3.1 VRP Description and Mathematical Model

As describes previously, according to different classification criteria, there are many different variants of the VRP problem. VRP problem in this paper is to study the problem of VRP standard, namely VRP with capacity limitation (Capacitated Vehicle Routing Problem, CVRP). The problem can be described as: from a distribution center, the goods are delivered to several distribution points by using several trucks. Each truck capacity is known and the same, the maximum mileage is known and the same, and the coordinate and goods demand of each distribution points are known. It requires

reasonable arrangement of distribution path, so the total mileage of all trucks is the minimum [10]. And it needs to meet the following limited conditions in the delivery process: each truck needs to be returned to the distribution center after finishing the goods delivery; the amount of cargo per truck loaded should not exceed the maximum capacity limit; all goods must be delivered; each distribution point can only be delivered by one vehicle; the length of each delivery route cannot be greater than the maximum mileage of each truck.

The graph theory of this problem is described as: for the complete graph  $G=(V,E)$ , the top point set is  $V = \{0,1,2,\dots,n-1,n\}$ , and the top point 0 represents the distribution center, the top point 1-n refers to n distribution points [11]. The edge set  $E = \{i,j|0 \leq i \neq j \leq n\}$  indicates the line between any two distribution points, and the edge length is represented as  $d_{ij}$ , indicating the distance of any two distribution points. Assuming that there are n trucks in the distribution center (No.1 to No.m), and the largest mileage of each truck is L, the capacity is Q, the goods demand of each distribution point is  $q_i (i = 1,2,\dots,n)$ , and  $q_i \leq Q (1 \leq i \leq n)$  [12].

Then the mathematical model of VRP is:

The target function is:

$$\min Z = \sum_{i=0}^n \sum_{j=0}^n \sum_{s=1}^m d_{ij} x_{ijs} \quad (6)$$

The constraint conditions are:

$$\sum_{i=1}^n q_i y_{is} \leq Q, S = 1,2,\dots,m \quad (7)$$

$$\sum_{i=0}^n \sum_{j=0}^n d_{ij} x_{ijs} \leq L, s = 1,2,\dots,m \quad (8)$$

$$\sum_{i=0}^n x_{ijs} = y_{is}, j = 1,2,\dots,n; s = 1,2,\dots,m \quad (9)$$

$$\sum_{s=1}^m y_{is} = \begin{cases} 1 & i = 1,2,\dots,n \\ m & i = 0 \end{cases} \quad (10)$$

$$\sum_{j=1}^n x_{ijs} = y_{is}, j = 1,2,\dots,n; s = 1,2,\dots,m \quad (11)$$

In the above model, (6) is the target function, representing that the total mileage of m vehicles is the minimum. (7) is the capacity constraint of each truck, and (8) is the mileage constraint of each truck, which will not be considered in some CVRP [13]. (9) constraints that each distribution point can only be delivered by a truck, and m trucks mutually coordinate to jointly complete all the delivery tasks. (10) and (11) constraint that there is only one truck that reaches or leaves a distribution point.

### 3.2 Results and Discussion

Experiment environment: Hardware environment: Processor of Pentium (R) Dual-Core CPU T4400 @ 2.20GHZ 2.20GHZ; Memory of 4G; Hard disk of 250GB. Software environment: Operating system of Windows7 ultimate; development environment of Matlab2010b; and development language of Matlab [14].

In order to verify the performance of improved drosophila algorithm, this chapter makes a simulation experiment of drosophila algorithm for solving CVRP problem. And the experimental results are compared with the original drosophila algorithm and other methods in the literature. The algorithm only discusses the situations of vehicle capacity limitation, but does not limit the delivery time or vehicle driving distance of each delivery point. As a result, the service time and route largest length in the data set are not used. At the same time, for better proving the good performance of drosophila algorithm in solving CVRP problems, five standard data sets Vehicle Routing Data Sets are selected, including an33k5 of 32 delivery points, bn45k5 of 44 delivery points, bn78k10 of 77 delivery points, pn101k4 of 100 delivery points and fn135k7 of 134 delivery points [15]. Moreover, the simulation experiment is carried out for the above five data sets.

**Table 2. Detailed information of five VRP standard data sets**

Data sets	Quantity of delivery stations	The largest capacity of vehicle	The number of vehicle
an33k5	32	100	5
bn45k5	44	100	4
bn78k10	77	100	10
pn101k4	100	400	4
fn135k7	135	2210	7

In the 5 data sets, we do the experiment for 20 times, and record the optimal results and average results. In the meanwhile, we compared the experimental results with original drosophila algorithm and algorithms in other literature [16]. The results showed that the improved drosophila algorithm, compared with the basic drosophila algorithm, can improve the solution accuracy indeed when solving CVRP problems.

#### 4 Conclusion

In this paper, we first of all introduce the research background and significance of vehicle routing optimization problem, and briefly introduce the basic theoretical knowledge of swarm intelligent system and basic concepts of drosophila algorithm. Then, in order to prove the validity of the proposed algorithm, drosophila algorithm is used to solve the TSP problem - typical combination optimization. Additionally, the algorithm is applied in the smell search and vision search. At last, to prove the performance of drosophila algorithm in solving TSP problems, and the simulation experiment is made for five data sets. What's more, the experimental results are compared with the algorithm in other literature. And it is obtained that the drosophila algorithm has better performance.

#### References

- [1] Malandraki, C., & Daskin, M. S. (2016). Time dependent vehicle routing problems: formulations, properties and heuristic algorithms. *Transportation Science*, 26(3), 185-200.
- [2] Kawamura, K., Kase, M., Ohno, M., Hashikawa, T., & Kato, M. (2015). Rich vehicle routing problems: from a taxonomy to a definition. *European Journal of Operational Research*, 241(1), 1-14.
- [3] Lai, M., & Tong, X. (2017). A metaheuristic method for vehicle routing problem based on improved ant colony optimization and tabu search. *Journal of Industrial & Management Optimization*, 8(2), 469-484.
- [4] Filipec, M., Krlec, D. Å., & Krajcar, S. (2015). Genetic algorithm approach for multiple depot capacitated vehicle routing problem solving with heuristic improvements. *International Journal of Modelling & Simulation*, 20(4), 320-328.
- [5] Hiermann, G., Puchinger, J., Ropke, S., & Hartl, R. F. (2016). The electric fleet size and mix vehicle routing problem with time windows and recharging stations. *European Journal of Operational Research*, 252(3), 995-1018.
- [6] Yao, B., Yu, B., Hu, P., Gao, J., & Zhang, M. (2016). An improved particle swarm optimization for carton heterogeneous vehicle routing problem with a collection depot. *Annals of Operations Research*, 242(2), 303-320.
- [7] Tharinee Manisri, Anan Mungwattana, Gerrit K. Janssens, & An Caris. (2015). A hybrid algorithm for the vehicle routing problem with soft time windows and hierarchical objectives. *Journal of Information and Optimization Sciences*, 36(3), 283-300.

- [8] Grangier, P., Gendreau, M., Lehuédé, F., & Rousseau, L. M. (2016). An adaptive large neighborhood search for the two-echelon multiple-trip vehicle routing problem with satellite synchronization. *European Journal of Operational Research*, 254(1), 80-91.
- [9] Bortfeldt, A., Hahn, T., Männel, D., & Mönch, L. (2015). Hybrid algorithms for the vehicle routing problem with clustered backhauls and 3d loading constraints. *European Journal of Operational Research*, 243(1), 82-96.
- [10] Grancy, G. S. D., & Reimann, M. (2016). Vehicle routing problems with time windows and multiple service workers: a systematic comparison between aco and grasp. *Central European Journal of Operations Research*, 24(1), 29-48.
- [11] Juan, A. A., Pascual, I., Guimarans, D., & Barrios, B. (2015). Combining biased randomization with iterated local search for solving the multidepot vehicle routing problem. *International Transactions in Operational Research*, 22(4), 647–667.
- [12] Wei, L., Zhang, Z., Zhang, D., & Lim, A. (2015). A variable neighborhood search for the capacitated vehicle routing problem with two-dimensional loading constraints. *European Journal of Operational Research*, 243(3), 798-814.
- [13] Mendoza, J. E., Rousseau, L. M., & Villegas, J. G. (2016). A hybrid metaheuristic for the vehicle routing problem with stochastic demand and duration constraints. *Journal of Heuristics*, 22(4), 539-566.
- [14] Hernandez, F., Feillet, D., Giroudeau, R., & Naud, O. (2016). Branch-and-price algorithms for the solution of the multi-trip vehicle routing problem with time windows. *European Journal of Operational Research*, 249(2), 551-559.
- [15] Chávez, J. J. S., Escobar, J. W., & Echeverri, M. G. (2016). A multi-objective pareto ant colony algorithm for the multi-depot vehicle routing problem with backhauls. *International Journal of Industrial Engineering Computations*, 7(1), 35-48.
- [16] Zhang, J., Lam, W. H. K., & Chen, B. Y. (2016). On-time delivery probabilistic models for the vehicle routing problem with stochastic demands and time windows. *European Journal of Operational Research*, 249(1), 144-154.