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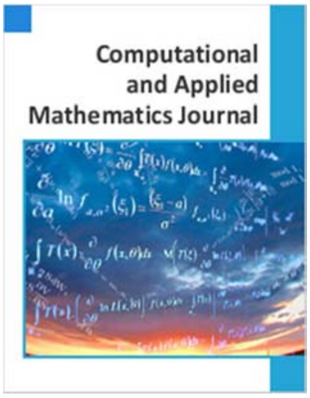

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Research on the Hybrid Fruit Fly Optimization Algorithm with Local Search for Multi-compartment Vehicle Routing Problem

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Abstract
With the rapid development of modern logistics industry, multi-compartment vehicle routing problem (MCVRP) is one of the research directions of vehicle routing problem, mainly to solve the problem of the transportation of non-mixed products in one vehicle. These products must be stored in separate compartments, and should not exceed the capacity of the carriage. A hybrid fruit fly optimization algorithm (HFOA) is proposed to solve the multi-compartment vehicle routing problem with capacity constraints, which combines three local search methods: 2-OPT, Swap and Insert. In HFOA, firstly, the initial feasible solution of MCVRP is constructed by using the stochastic method. Secondly, from the initial solution, the path probability function is used to create the fruit fly path. Then, three local search methods are used to optimize the path, and the optimal solution is used to update the trajectory strength of the distribution network. To improve the search efficiency, the local search process is only implemented in one iteration. Based on the simulation results of 7 benchmark problem, it is found that the HFOA algorithm can produce better path planning than traditional methods.

1. Introduction

With the rapid development of modern logistics industry, there are two characteristics in logistics distribution. Firstly, the types of products to be transported are numerous and complicated; Secondly, demand for transportation is increasing rapidly. In the logistics distribution system, the path length of the vehicle is one of the most important factors that affect the total cost. Logistics enterprises must strengthen the vehicle routing optimization for transportation and distribution, to improve the efficiency of logistics and reduce logistics costs. Therefore, the vehicle routing problem (VRP) is widely concerned by the industry workers and researchers. In recent years, considering some practical constraints such as vehicle has multi compartment and products cannot be mixed, multi-compartment vehicle routing problem (MCVRP) with capacity constraints has become a research hotspot.

Since Dantzig and Ramser, the VRP problem has been a hot topic in operations research [1]. With the development of the research, some methods, such as the computer simulation, the logistics planning and so on, are applied gradually, and a lot of research results have been obtained. Due to the traveling salesman problem (TSP) is a special case of the VRP problem, and it has been proved to be NP problem [2], therefore, VRP and MCVRP are also NP hard problem. The traditional mathematical optimization algorithm is difficult to solve the large-scale NP problem. Therefore, heuristic algorithm is one of the most important methods to solve the VRP problem in a short time to get a better solution. In recent years, fruit fly optimization algorithm (FOA) has been paid more and more attention by scholars.

The FOA is a population evolutionary algorithm proposed recently [3]. Different from the original optimization algorithm, the FOA has some characteristics such as simple operation, easy to understand, easy to implement, and so on. At present, FOA has been studied and applied in continuous optimization problems such as finance, electric power load forecasting, logistics service, parameter tuning, and so on [4]. However, just like other global optimization algorithms, FOA is easy to fall into local optimum. The convergence speed is slow and the convergence precision is reduced in the later stage of the search. Therefore, some scholars have improved the optimization algorithm through some methods, such as chaos theory [5] and bacterial chemotaxis algorithm [6].

Although the FOA and its improved algorithms show the better optimization effect for some test functions, the former researches are mainly about continuous space optimization problems. However, the research for discrete space optimization problems, such as combinatorial optimization problem, is still less. Therefore, this paper uses the FOA to solve the discrete VRP. A hybrid FOA (HFOA) is presented in this paper based on the multi-compartment vehicle and local search.

The structure of this paper is as follows. The current research situation of VRP problems are reviewed in the second part. The MCVRP is modeled in the third part. Based on the local search, the HFOA is proposed in the fourth part. In the fifth part, the performance of HFOA is also tested by using the method of computational experiments. Some conclusions are given in the end.

2. Literature Review

VRP is a problem like this: to transport products stored in the warehouse center, a fleet of vehicles starts from the warehouse to customers for distributing products, to meet the customer needs and to minimize the cost of all the vehicle's total transportation. VRP was first proposed by Dantzig and Ramser, which can be regarded as a generalized form of traveling salesman problem (TSP). During the application process of VRP, the vehicle routing problem with capacity constraints (CVRP) is beginning to emerge due to the limitation of vehicle transport capacity. In CVRP, a fleet of vehicles in which every vehicle has a constant capacity Q serve a certain number of customers, and each customer has a fixed transportation demand. Each vehicle accesses each customer only once, and the total amount of customer requirements assigned to any paths does not exceed the capacity of the vehicles. The goal of the CVRP problem is to minimize the total distance traveled by all vehicles.

With the in-depth study, facing multiple product transport requirements of customers, MCVRP is proposed to deal with customer demand of transportation problems of different types of products. The demand of each customer for each product is fixed and known in advance. Different products must be stored in different compartments of the same vehicle during transportation. Each vehicle has a fixed number of compartments, and each compartment has a certain capacity limit. In the process of assigning a customer to a transport path, the total demand of customer for any product does not exceed the capacity of the vehicle to store the product. The goal of the MCVRP problem is to minimize the total transportation distance.

When a variety of products are transported together and cannot be mixed, the multi-compartment configuration is essential. In fact, in many industries, different products must be handled separately using a multi-compartment vehicle. For example, in the garbage collection, garbage classification can reduce the total recovery costs, including transportation and processing. Some vehicles can transport some classifying garbage from the storage point to the recovery area. It needs different compartments to complete the transportation task. Today, in most cities, the governments have provided some independent garbage boxes for garbage collection, so the solution of MCVRP is imminent now.

In industry applications, an application of MCVRP is the transportation of foods, which the refrigerated foods and non-refrigerated foods are stored in different compartments in the same vehicle. Based on the vehicle with two different compartments, Chajakis and Guignard resereached two integer programming models, and discuss the decision process of assigning the customer to the transportation route [7]. Another application of MCVRP is to use different capacity tanks to transport different types of fuel at the same time. To solve this problem, Avella et al. studied a branch and bound algorithm based on set partitioning algorithm [8]. EI Fallahi et al. studied a memetic algorithm and tabu search algorithm, to solve the problem of multi tank transportation [9].

Many scholars have applied local search and heuristic algorithm to MCVRP problem. For the vehicle routing problem with capacity constraints in logistics distribution, Chen et al. proposed an iterative local search algorithm based on multi neighborhood [10]. By comparing the multi-compartment vehicle with the single compartment vehicle, Muyldermans and Pang have studied the benefits of classifying garbage to be transported from different locations to the center by the multi-compartment vehicle. Based on some local search methods such as the 2-OPT, crossover, swap and redistributing paths, they use local search procedures to solve the problems, and compare the results with the research results of EI Fallahi [11]. Avella et al. assumes that each customer's demand for certain products cannot be split. However, they assume that multiple vehicles can access the same customer to meet the needs of different products. Reed et al. proposed an improved ant colony system (ACS) with 2-OPT local search to solve the basic CVRP problem in garbage collection network [2]. The improved algorithm can solve the MCVRP problem that each customer can be accessed only once by a vehicle. Gajpal and Abad proposed a AC algorithm to solve the VRP with the simultaneous transmission [13]. Balseiro et al. tried to combine the interpolation method with AC algorithm to solve the VRP problem with time window constraints [14]. De La Cruz et al. proposed a sequential algorithm with AC and tabu search to solve the VRP problem with time window constraints, in which heterogeneous vehicles can transport a variety of products [15]. Tan et al. designed a heuristic algorithm which combines the ACS and 2-OPT method to solve the vehicle routing problem [16]. These results show that the heuristic algorithm is very effective to solve the VRP problem and its deformation problem.

Inspired by Reed et al. algorithm, the MCVRP is extended by using multi compartment of the vehicle. The new MCVRP problem is that some vehicles start from the central warehouse to the customer, to distribute various types of products at the same time, and these products are stored in different compartments in the same vehicle during the process of transportation. Use a vehicle fleet of the same vehicle; each vehicle access to a group of customers; each customer can be accessed only once by a vehicle. The problem to be solved is to determine which customers are assigned together in a single transport, and to determine the order in which they are accessed by minimizing the total travel distance. The purpose of this paper is to improve the existing FOA by combining with local search to solve the MCVRP.

3. The Model of MCVRP

Considering the logistics distribution network, the MCVRP problem can be described as following. There is a single distribution center (warehouse) and some customers who need distribution services in distribution network. Each customer has a variety of products to be delivery and the demand of each product is fix. A fleet of the vehicle with multi-compartment, and each compartment has fixed capacity. The distances between nodes of distribution network are known. These vehicles service customers to deliver many kinds of products. Each customer can access only once by a vehicle. Every vehicle starts from the distribution center, access some customers, and finally return to the distribution center. The problem is that obtaining the route of each vehicle to minimize the total transport distance.

To describe the math model of MCVRP, some symbols associated with it are listed in table 1.

Table 1. *Some symbols and their meaning used in MCVRP model.*

symbol	meaning	symbol	meaning
V	The vertex of distribution network, including customers and distribution centers	q_{ip}	Number of product p that customer i need to transport
A	Adjacency matrix of distribution network	Q_p	The carriage capacity of the product p
C	Vertex distance matrix of distribution network	L	Maximum length for any path
N	Set of customers	c_{ij}	Length of arc (ij)
K	Set of vehicles	x_{ij}^k	If vehicle k accesses to customer j after visiting customer i , $x_{ij}^k=1$
p	Set of products, which is equal to the set of compartments in a vehicle	Q_{ip}^k	The total transport capacity of the product p after vehicle k leaves customer i

The undirected graph $G=(V,A,C)$ is used to describe the distribution network of MCVRP formally. The set of vertexes in graph G is $V=\{i \mid i=0,1,...,n\}$, in which the zero vertex is distribution center (warehouse), and they are customers which served by k vehicles. $A=\{(i,j) \mid i,j\in V\}$ is the set of arcs which connect the points in network. The vehicles are the same, and locate in distribution center (warehouse) at the beginning. There are p compartments for each vehicle. The number of compartment is equal to the number of products which need to be distributed in logistic network. For every product p, there are q_{ip} products to be deliver for customer i. Each customer can be access by a vehicle only once. Each vehicle has a sequence of customer which is accessed orderly. For a given product, the total demand of the sequence of customer cannot exceed the capacity Q_p of the compartments. The max length of every path cannot exceed L. $C=\{c_{ij} \mid (i,j)\in A\}$ is the distance matrix of network, c_{ij} is the distance from customer i to j. Suppose that the distance matrix is symmetric, i.e. $c_{ij}=c_{ji}$.

Let x_{ij}^k be a binary variable, $x_{ij}^k=1$ if and only if vehicle k access customer j after accessing customer i. Let Q_{ip}^k be the total transportation of product p after vehicle k leaves vertex i. Therefore, the formula of MCVRP are as following:

$$\text{Min} \quad Z=\sum_{k\in K}\sum_{i\in V}\sum_{j\in V} c_{ij}x_{ij}^k \tag{1}$$

s. t.

$$\sum_{k\in K}\sum_{j\in N} x_{ij}^k=1, \tag{2}$$

$$\sum_{k\in K}\sum_{i\in N} x_{ij}^k=1, \quad \forall j\in N \tag{3}$$

$$\sum_{i\in N} x_{0i}^k=\sum_{j\in N} x_{j0}^k=1, \quad \forall k\in K \tag{4}$$

$$q_{ip}\le Q_{ip}^k\le Q_p, \quad \forall i\in N, k\in K, p\in P \tag{5}$$

$$Q_{ip}^k - Q_{jp}^k + Q_p x_{ij}^k \le Q_p - q_{jp}, \quad \forall i \in N, k \in K, p \in P \tag{6}$$

$$\sum_{i \in V} \sum_{j \in V} c_{ij} x_{ij}^k \le L, \quad \forall k \in K \tag{7}$$

$$x_{ij}^k \in \{0,1\}, \quad \forall i \in V, j \in V, k \in K, \quad i \ne j \tag{8}$$

Equation (1) is the objective function that represents the total distance of all vehicles on all routes; Equation (2) and (3) indicate that a path can enter and leave a vertex only once. They work together to ensure that only one vehicle access to a customer only once. Equation (4) ensures that each vehicle starts its path from 0 point at the end of 0 point (warehouse). Equations (5) and (6) are necessary for the elimination of sub loops, which satisfy the capacity requirements and connection requirements between the two customers. If $x_{ij}^k = 0$, equation (6) is not required due to $Q_{ip}^k \le Q_p$ and $q_{jp} \le Q_{jp}^k$. If $x_{ij}^k = 1$, Equations (5) and (6) make sure that $Q_{ip}^k - Q_{jp}^k \le -q_{jp}$, which eliminate the sub loops. In addition, the equation (5) ensures that the total transport capacity is not exceeded the vehicle capacity for products after it accesses the vertex *i*. Therefore, the equation (5) ensures the constraints of ability. Equation (7) shows the constraint of path length. Equation (8) describes the variable x_{ij}^k, which is equal to 1 if and only if vehicle *k* access customer *j* after accessing customer *i*.

4. Hybrid Fruit Fly Optimization Algorithm

The FOA is used to find the optimal solution for NP hard problem. Based on the olfactory and visual capability of true fruit flies in the process of searching food, FOA updates the status of fruit flies by searching the global optimum. In the iterative computations, once a fruity-fly find a better global optimal, all individuals in the fruit fly melanogaster population gather to its location. The mechanism of individual update, on the one hand, makes everyone's own information to be not shared and inherited, then reduced the diversity of the population; on the other hand, the position may be not the global optimal, which makes the algorithm easy to fall into the local optimal point, resulting in premature convergence [17]. Zheng Xiaolong proposed a novel hybrid discrete algorithm for permutation flow scheduling problem. The evolution of each generation in the algorithm consists of four stages: olfactory search, visual search, cooperative evolution and annealing process [18]. Based on the advantages and disadvantages of the FOA, this paper proposes HFOA for the multi-compartment vehicle routing problem.

4.1. Algorithm Idea

In the iterative process of HFOA, the update of individual status does not only follow the current best individual, but also learn from the local optimum, then the path strength should be updated. Therefore, it ensures the fruit flies aggregate to the global optimal position, and learns and inherits the local optimum information at the same time.

Overall, the HFOA has three steps as following:

Step 1: Create the initial solution, and initialize the trajectory strength of path.

Step 2: Repeat the following operations until the termination condition.

Step 2.1: Create route for m fruit flies.

Step 2.2: Perform local search, to improve solutions generated by each fruit fly.

Step 2.3: Update the best solution.

Step 2.4: Update strength of track for all arcs by using the best solution.

Step 3: terminate the algorithm and report the best solution.

In the HFOA, Fruit fly is used to construct route solutions for MCVRP. During each iterative process for the construction of route, each fruit fly performs four basic activities step by step: (1) it selects the next customer based on the probability function of route attraction; the route attraction consists of two aspects: strength of taste and strength of trajectory; (2) it accesses to the tabu list of customer in the current route; (3) it updates the residual capacity of the compartment of the vehicle; (4) it updates the trajectory strength of arcs which have been accessed. Then, the local search procedure is used to improve the quality of the solution. Finally, the tabu list is deleted and a new iteration starts.

To describe the optimization process of HFOA, the following symbols used in HFOA are shown in table 2.

Table 2. *the meaning of symbols in HFOA.*

symbol	meaning	symbol	meaning
m	Number of fruit flies	N_i	List of all possible customers which are not accessed by fruit fly
μ_{ij}	The strength of taste, that is, the reciprocal of path ij length	τ_{ij}	The strength of track, that is, the access times of path (ij)
ε_{ij}	The attractive value of path (ij)	p_{ij}	The probability that a customer j will be accessed after the customer i is accessed by a fruit fly.
q	Random variables, to determine whether the customer choice is based on attractive probability or the biggest attraction.	q_0	Threshold of q
L^{best}	The length of the best solution found so far	ρ	Persistence coefficient of path
$Tabu_s$	The tabu list of customers firstly visited by all fruit flies	$Tabu_i$	The tabu list of customers which are accessed by fruit fly i.

4.2. Initialization

The first step of the HFOA is to generate the initial solution and initialize the trajectory strength of each path. The method of generating the initial solution is as follows: firstly, according to the topological structure of the network, the customers are randomly generated, and then, if the carrying capacity of the vehicle is enough to meet the needs of the customers, the customers are randomly added to the vehicle path. Otherwise, before accessing the next customer, the vehicle returns to the warehouse. The flowing chart shows the process of initialization path in figure 1.

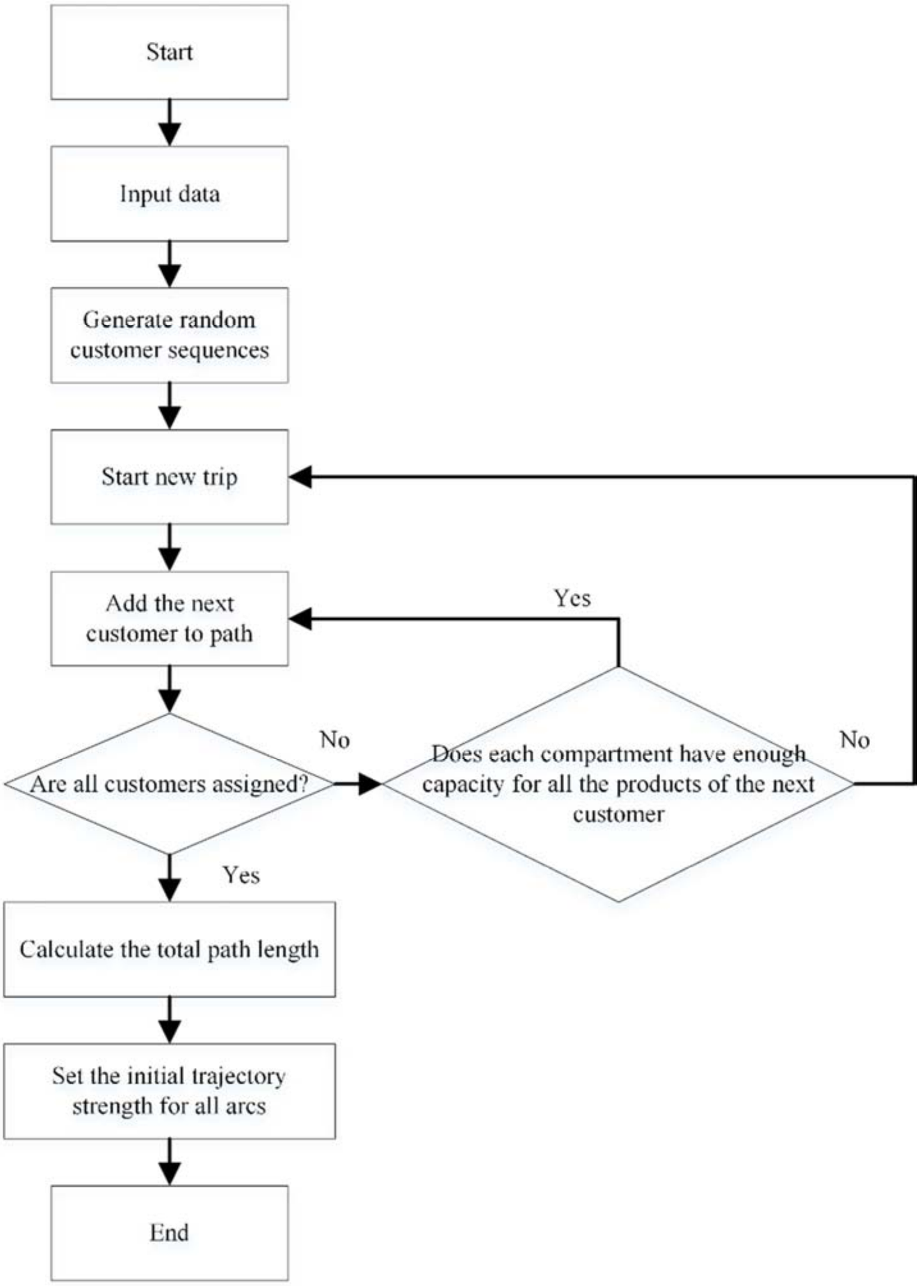

Figure 1. *The process of path initialization in HFOA.*

4.3. Route Creation

Suppose that there are *m* fruit flies in HFOA. Each fruit fly generates a complete route (i e., a complete MCVRP solution). Each fruit fly starts from the warehouse, and selects the first customer randomly (different fruit fly may select different customer also). The purpose of the first customer selected randomly is to diversify the solution. Then, based on the track intensity and taste intensity of arcs, each fruit fly moves from one customer to another by proportional to the probability of path attraction.

In the FOA, the intensity of taste is the reciprocal of the distance between the current location and the origin of the fruit fly. In this paper, the inverse of the distance between the next customer to search and the current location is taken as the taste strength. Obviously, the shorter the distance is, the greater the strength of taste is, then fruit flies are more likely to choose customers whose distance is smaller, to achieve the goal of minimizing the path length.

Therefore, the arc ij attraction power includes two parts: the first is the strength of track τ_{ij}, which is the frequency of arc ij accessed during iterative process; the second is the strength of taste μ_{ij}, i.e., the reciprocal of arc ij length, which represents the moving tendency of fruit fly from i to j. Attractive power value can be calculated as follows:

$$\varepsilon_{ij} = (\tau_{ij})^{\alpha}(\mu_{ij})^{\beta} \tag{9}$$

Where, α and β are the power indexes, which indicate the influence of track strength and taste strength respectively. The probability P_{ij} means that the customer j will be the next customer after the fruit fly visits the customer i:

$$p_{ij} = \begin{cases} \dfrac{\varepsilon_{ij}}{\sum\limits_{l \in N_i} \varepsilon_{il}} & j \in N_i \\ 0 & j \notin N_i \end{cases} \tag{10}$$

Where, N_i is the list of all viable customers that have not been accessed by the current vehicle, and do not exceed the vehicle capacity. Equation (10) shows that the choice probability of the next customer is proportional to the arc ij attraction.

To speed up the convergence rate of the algorithm, this paper proposes a threshold control mechanism for choosing customer. That is, a random variable q that is evenly distributed on the [0,1] is generated before each fruit fly chooses the next customer j according to the equation (10). If $q > q_0$, select the next customer according to the equation (10), otherwise select the customer on the most attractive arc. q_0 is a given constant threshold, indicating whether the next customer choice is determined according to equation (10).

Each fruit fly continues to add customers in accordance with the above rules until there are no more viable customers (N_i is empty). Then, the fruit fly goes back to the warehouse and begins another transportation route. If the first customer in the transport route is selected according to the formula (10), the first customer on the route is the neighbor node of the warehouse, which can reduce the diversity of customer search.

4.4. Local Search

Inspired by the Lin study [19], each travel of a fruit fly is considered as a TSP, so it is possible to reduce the transportation distance by adjusting each route to ensure that it does not exceed the capacity limit. Therefore, after the creation of all the lines, three local search procedures are implemented to improve the quality of the solution.

To expand the local search scope, three different local search methods are used in the HFOA, such as: 2-OPT, Swap and Insert.

1) 2-OPT. A 2-OPT local search can be described as follows: the route breaks at two points to form three segments. The customer sequence in the middle part is inverted. By connecting the new three segments, the new route is reconstructed. Suppose that i and j are two non-adjacent customers on a route, i^+ and j^+ are next adjacent nodes in the path respectively. 2-OPT is that deleting arc (i,i^+) and (j,j^+), and adding arc (i,j) and (i^+,j^+), so a new path is obtained.
2) Swap. The locations of two customers i and j are exchanged each other in the current route set to generate a new set of routes. Notice that, i and j may belong to the same path, or belong to different paths.
3) Insert. Customer i is moved from location p_1 to another location p_2 to generate a new set of feasible routes in the current route set. Notice that, p_1 and p_2 may belong to the same path, or belong to different paths.

After trying all possible local search such as 2-OPT, Swap and Insert, all feasible solutions are obtained. Then the shortest route can be chosen from them.

4.5. Updating the Strength of Track

The purpose of local search is to improve the quality of solutions produced by fruit fly. After the local search of each iteration, the optimal solution is found to update the trajectory strength of all arcs. In addition, the way that the strength of the arc trajectory decay with time is used to simulate the actual situation.

Updating the track strength includes two steps: the strength of all the arc trajectory is reduced to simulate the decay intensity firstly; secondly, only to increase strength of the best route trajectory arc, which drive the flies more likely to choose the shortest path. ρ is defined as the coefficient of trajectory persistence, $0 \le \rho < 1$, then $1-\rho$ can be explained as the decaying ratio of the intensity of track during the iteration. Then, the updating formula of the strength of arc ij (track) is as following:

$$\tau_{ij}^{new} = \begin{cases} \rho\tau_{ij}^{old} + 1/L^{best} & ij \in best\ route \\ \rho\tau_{ij}^{old} & other \end{cases} \tag{11}$$

Where, L^{best} is the total length of the best route in each iteration. In the equation (11), the product of the trajectory intensity and ρ represents the residual strength of the trajectory after the decay, and then the trajectory strength of the optimal route is updated by adding $1/L^{best}$ to the residual amount to the decay intensity.

Combined with the above steps, the process of HFOA is shown in figure 2.

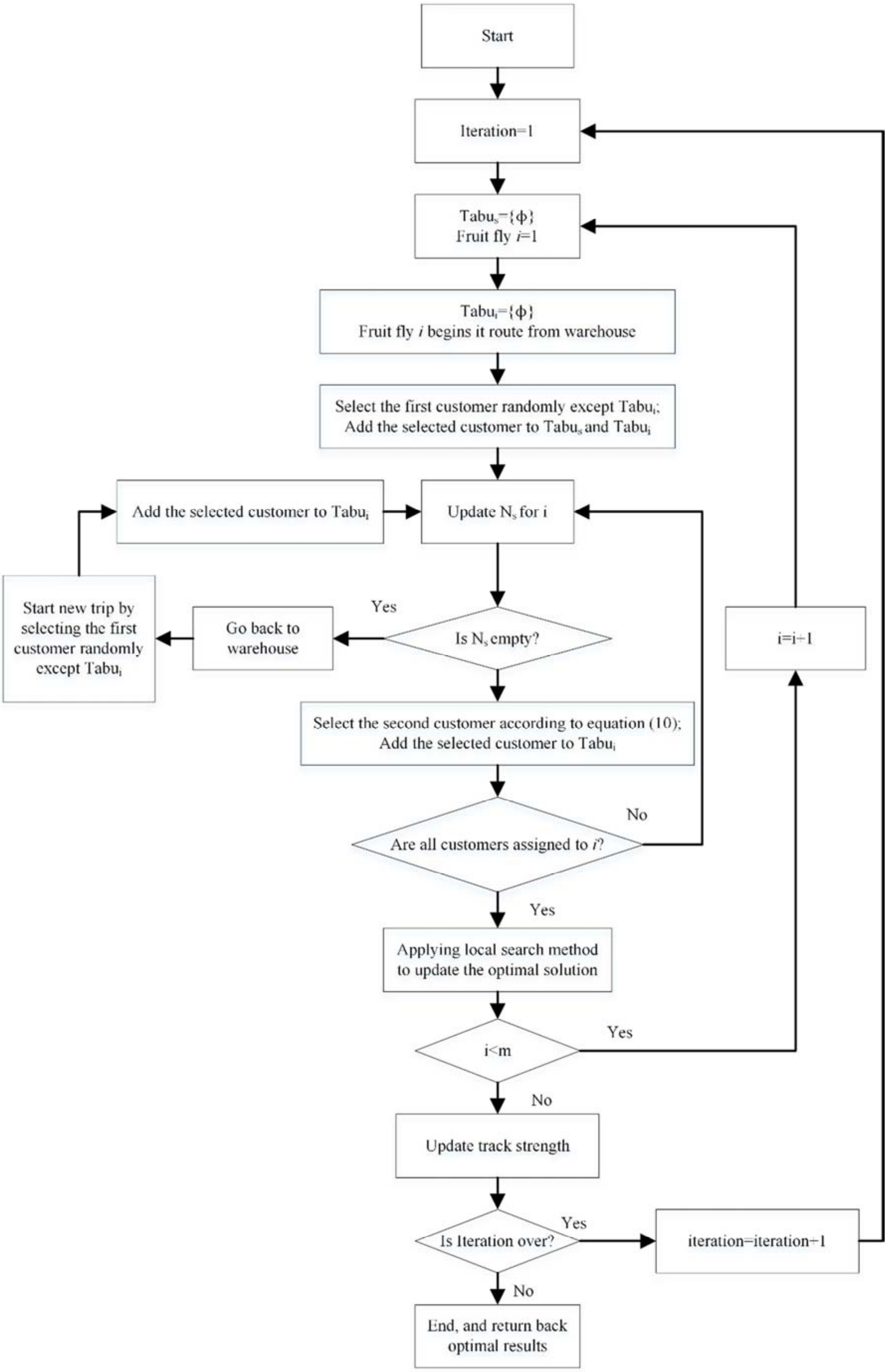

Figure 2. The process of HFOA for MCVRP.

5. Simulation and Comparison

5.1. Test Data and Parameter Settings

To test the effectiveness of the HFOA, this paper adopts Benchmark problem proposed by Christofides Mingozzi, and Toth [20], and then compares the results with the ACS algorithm proposed by Lin [21] and the HAC proposed by Abdulkader [22]. Considering the conditions of capacity constraint, only 7 of 14 Benchmark problem are chosen in this paper, in which customer positions are randomly distributed evenly in problem VRPNC1~VRPNC5, and customer locations are aggregated distribution in the problems VRPNC6~VRPNC7. The number of customers in these problems is between 50~199.

Suppose that each vehicle has two compartments. The total capacity of each vehicle in the original data is divided into the capacity of two compartments according to 1:3. That is, if the vehicle capacity is Q in the original data, then the capacity of two compartments in the new data are $0.25Q$ and $0.75Q$.

Although the number of fruit flies in the HFOA determines the quality of the best route, it also affects the computation time. After many tests, $m = 20$. Other parameters are: $\alpha = 1$, $\beta = 2$, $\rho = 0.9$, $q_0 = 0.9$. The experiment takes 100 iterations.

5.2. Effectiveness Analysis of HFOA

The Matlab program is used to simulate ACS, HAC and HFOA algorithm. The results are shown in table 3. At the same time, the improvement percentages of the total path length are shown in table 3.

Table 3. *Simulation results of MCVRP's 7 Benchmark problem*

Problem	Number of customer	Total length of ACS	Total length of HAC	Total length of HFOA	(ACS-HAC)/ACS (%)	(ACS-HFOA)/ACS (%)
Vrpnc1	50	569.564	550.7	551.27	3.31	3.21
Vrpnc2	75	957.525	890.68	886.24	6.98	7.44
Vrpnc3	100	964.132	874.07	870.13	9.34	9.75
Vrpnc4	150	1253.86	1126.12	1130.65	10.19	9.83
Vrpnc5	199	1587.02	1444.29	1440.78	8.99	9.21
Vrpnc6	120	1133.88	1110.45	1109.42	2.07	2.16
Vrpnc7	100	911.861	912.64	910.73	-0.09	0.12
Average		1053.977	986.99	985.60	6.36	6.49

The results in Table 3 show that the average total length of ACS is 1053.977 unit length, the average total length of HAC is 986.9929 unit length, and the average total length of HFOA is about 985.6029 unit length. The average total length of HAC is improved by 6.36%, and the average total length of HFOA to HAC is improved by 6.49%. These results show that the HFOA proposed in this paper is similar to HAC, and can get a better-quality path than ACS algorithm. This verifies the dominant position of heuristic algorithms in existing optimization algorithms. The HFOA is slightly higher than the HAC algorithm in the route length, mainly due to the strong local search ability of the algorithm.

For the problem VRNPC6 and VRNPC7, the difference of the total length is very small in HFOA, HAC and ACS. The reason is that customers are clustered on these issues, so the path length improvement is limited.

Comparing the number of customers in these problems, the overall length of the path becomes better with the number increase of customers can be found, from 3.21% of 50 customers to 9.83% of 150 customers. This trend means that as the size of the problem increases, the effectiveness of the HFOA and HAC algorithms are increased. It can be concluded that HFOA and HAC have a good effect on large scale problems. Because many local search methods are used in HFOA and HAC, Fewer iterations can get a better route, but the local search also consumes a certain amount of computing time.

5.3. Analysis of the Effectiveness of Local Search

To observe the effectiveness of local search for the HFOA, this paper uses different combinations of three kinds of local search methods to solve MCVRP, and compares their results with the results of FOA algorithm without local search. In the first combination, only 2-OPT local search is combined with FOA algorithm. In the second combination, 2-OPT and Swap search are combined with the FOA algorithm. In the third combination, three local searches, such as 2-OPT, Swap and Insertion, are all combined with FOA. For each combination, the different number of iterations can be calculated to maintain the approximate computation time. The results are shown in table 4. The results show that the FOA algorithm with hybrid local search is very effective to shorten the optimal path length of MCVRP.

Table 4. *The results of mixed local search in FOA.*

Algorithm	Number of iteration	Average path length	%
FOA	10,000	1189.78	-
2-Opt+FOA	10,000	1048.7	11.86
2-Opt+Swap+FOA	300	1034.61	13.04
2-Opt+Swap+Insert+FOA	100	985.6	17.16

From table 4, the combination of local search can effectively improve the results of HFOA algorithm. When the

2-OPT local search is combined with FOA, the result quality is improved by 11.86%. However, 2-OPT local search is not enough to improve the quality of the program. Because 2-OPT local search is only applied to a single trip, so its performance is good for TSP, but its performance is limited for VRP. When FOA is combined with 2-OPT and Swap search, the result quality is increased from 11.86% to 13.04%. This result shows that the quality of the solution can be improved by the fact that the swap can move the customer on two paths. Finally, the quality of the results is increased from 13.04% to 17.16% when the Insertion, 2-OPT, and Swap are combined with FOA. The results show that the local search is very effective in improving the quality of the results.

5.4. Advantage Analysis of Multi-compartment Vehicle

To analyze the advantages of multi-compartment vehicle, this paper uses two methods to solve the Benchmark problem. In the first mode, the transport vehicle has only one compartment with a capacity Q. In the second way, each vehicle has two compartments, which have the capacity of Q_1 and Q_2. In the second way, the total capacity of the vehicle remains the same with the first way, that is $Q = Q_1 + Q_2$.

Because the two kinds of products cannot be mixed for customer, in the first way, a customer can be accessed two times on different paths respectively to transport product 1 and 2. In this case, the VRP is decomposed into two sub problems. The VRP for product 1 and product 2 could be solved respectively. The sum of the shortest paths of these two sub-problems is the result of the first method. For two ways, the results of the 7 problems are shown in table 5.

Table 5. *Comparison Analysis of the results of vehicle with different compartments.*

Problem	Number of customer	Total length of vehicle with two compartments (A)	Total length of vehicle with one compartment (B)	(B-A)/A*100
vrpnc1	50	551.27	935.32	69.67
vrpnc2	75	886.24	1319.33	48.87
vrpnc3	100	870.13	1432.56	64.64
vrpnc4	150	1130.65	1719.16	52.05
vrpnc5	199	1440.78	2037.73	41.43
Vrpnc6	120	1109.42	1573.89	41.87
Vrpnc7	100	910.73	1279.78	40.52
Average		985.60	1471.11	49.26

From table 5, the total length of the path increases significantly when there is only one compartment. Because in this case, a customer is visited two times to transport the different products of two categories. Two times to visit a customer increase the total transport distance. In the second way, as the number of compartment increases, the vehicle can serve more customers on each route, thus reducing the total length of the transport path. From table 5, the average total length of the vehicle with single compartment is increased by 49.26% compared with the vehicle with two compartments, which shows that the multi-compartment vehicles have certain advantages compared with the single compartment vehicles.

6. Conclusions

Local search algorithm is an important method for solving combinatorial optimization problems. Combined with three types of local search methods, the HFOA is proposed to solve the multi-compartment vehicle routing problem. The effectiveness of HFOA is verified by using 7 Benchmark problems. From the numerical experiments, the HFOA has improved its performance for all the problems, and have a good effect on a large scale. Numerical experiments also show that the combination of local search and FOA algorithm is very necessary. At the same time, this paper also analyzes the advantages of multi-compartment vehicles.

Compared with the results of HFOA and HAC algorithm, they both effectively shorten the effective path of the MCVRP, but the difference is not large. How to improve the combination of local search algorithm and FOA is needed further study in the future.

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