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Hybrid fruit fly optimization algorithm for solving multi-compartment vehicle routing problem in intelligent logistics

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A B S T R A C T

The purpose of this study was to tackle multi-compartment vehicle routing problem in intelligent logistics with the fruit fly optimization algorithm (FOA). A hybrid FOA (HFOA) integrated with three local search methods (2-opt, swap and insert) was adopted to solve the multi-compartment vehicle routing problem (MCVRP) in intelligent logistics by applying discrete space optimization problems. The numerical experiments show that the HFOA algorithm has improved the performance for all proposed problems, including improving the total path length and enhancing the solution quality. The improvement rate in total path length shifts from 3.21 % at 50 customers to 9.83 % at 150 customers indicating that this HFOA is more effective in largescale. The HFOA integrated with 2-opt, swap and insertion elevates the solution quality from 11.86 % to 17.16 % displaying the advantages. The effectiveness and stability of the proposed algorithm shed new light on the routing of MCV distribution problems in intelligent logistics.

A R T I C L E   I N F O

Keywords:
Intelligent logistics;
Vehicle routing problem (VRP);
Multi-compartment vehicle (MCV);
Bionic optimization;
Fruit fly optimization algorithm (FOA)

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1. Introduction

Intelligent logistics is a modern comprehensive logistics system supported by information technology. It realizes system perception, comprehensive analysis, timely processing and self-adjustment in transportation, warehousing, packaging, handling, circulation processing, distribution, information service and so on. In the modern logistics industry, the logistics distribution carries two main features: the various and numerous products to be transported, and the rapidly increasingly transport demand. For a distribution system, the total cost relies heavily on the path length of the vehicle. In light of these, vehicle routing must be optimized to enhance the transport efficiency and lower the distribution cost. This contributes to the focus on the vehicle routing problem (VRP) in the intelligent logistics industry and the academia.

Since 1959, the VRP has always been a hot topic in operations research (Dantzig and Ramster) [1]. Over the years, computer simulation, logistics planning and many other strategies have been introduced to the VRP research, yielding fruitful results. Recent years has seen the rise of the multi-compartment VRP (MCVRP) with capacity constraints. This problem mainly considers the multiple compartments of the vehicle, and ensures the separation between different products.

Both the VRP and the MCVRP are NP-hard problems, for the traveling salesman problem (TSP), a special case of the VRP, has been proved as NP-hard (Garey, 1979) [2]. It is difficult to solve a large-scale NP-hard problem with traditional mathematical optimization algorithm.

Hence, more and more attention has been paid to bionic optimization, especially the fruit fly optimization algorithm (FOA), aiming to find a good solution to the VRP in a short time.

Unlike traditional optimization algorithm, the bionic optimization, such as the FOA, is an emerging evolutionary algorithm, which is easy to understand, operate and implement. It has been applied to many continuous space optimization problems, namely, finance, electric load forecast, logistics service, and parameter tuning [4-6]. Nevertheless, the FOA, as a global optimization algorithm, is prone to the local optimum trap. The convergence is particularly slow and inaccurate in the later stage of the search. To solve the defect, some scholars have adopted the chaos theory [7] and bacterial chemotaxis algorithm [8] to improve the FOA.

Despite the good effect of the FOA and its improved versions, the existing research emphasizes continuous space optimization problems over discrete space optimization problems like the combinatorial optimization problem. To make up for the gap, this paper attempts to solve the discrete vehicle routing problem by a hybrid FOA (HFOA) based on the MCV and local search.

The remainder of this paper is organized as follows: Section 2 reviews the previous research on the VRP, and presents some solutions to the MCVRP; Section 3 details the model of the MCVRP; Section 4 presents the HFOA based on the local search; Section 5 verifies the effect of the HFOA through computational experiments; Section 6 wraps up this paper with some meaningful conclusions.

2. Literature review

The vehicle routing problem is a type of optimal scheduling problem that studies how to optimize the transportation cost by rationally planning the driving route. Its related theories and algorithms have important application value for reducing logistics costs, so it has always been a research hotspot in the field of operations research and combinatorial optimization. Over the years, vehicle routing problems have spawned numerous research branches, such as open vehicle routing problems, multi-site vehicle routing problems, loading and unloading vehicle routing problems, vehicle routing problems with time windows, and periodic vehicle routing problems. And have obtained a lot of research results, At the same time, the vehicle routing problem is also widely used in all aspects of production and life, such as letter delivery, cargo distribution, vehicle scheduling, etc., which has produced huge economic benefits.

As a generalized form of the TSP, the VRP (Dantzig and Ramser, 1959) aims to transport products from the distribution centre (warehouse) to customers with a fleet of vehicles, and fulfil customer demands at the minimal cost. In the course of application, the VRP with capacity constraints (CVRP) emerges due to the limited transport capacity of vehicles. To minimize the total distance covered by all vehicles, the CVRP assumes that each vehicle has a constant capacity Q to serve a fixed number of customers, each of which has a fixed demand, that each vehicle accesses each customer only once, and that the total demand on any path does not surpass the vehicle capacity.

Considering the varied transport requirements of customers, some scholars have presented the MCVRP under the following premises: each customer has a fixed and known demand for each product, different products are stored in separate compartments of the same vehicle during transport, each vehicle has a fixed number of compartments, and each compartment has a certain capacity limit. In addition, the total customer demand for any product should not exceed the capacity of the vehicle that carries the product, when a customer is assigned to a distribution path. The goal of the MCVRP is also to find the minimal total distance of distribution.

The multi-compartment configuration is essential to transporting various products that cannot be mixed together all at once. For example, the MCVRP has been applied to the transport of food. The refrigerated foods and non-refrigerated foods are stored in different compartments of the same vehicle. Chajakis and Guignard (2003) explored two integer programming models of two-compartment vehicles, and discussed the decision-making of assigning the customer to the distribution path [9]. The MCVRP has also been applied to the transport of fuels, such that different types of fuels are stored in tanks of varied capacities. For instance, Avella *et al.* (2004) developed a branch and bound algorithm based on set partitioning [10]. Fallahi *et al.* (2008) solved multi-tank transport [11] with memetic algorithm and tabu search algorithm.

For better performance, the MCVRP has been frequently enhanced by local search and heuristic algorithm. Focusing on the CVRP, Chen *et al.* (2009) proposed an iterative local search algorithm based on multiple neighbourhoods [12]. Muyldermans and Pang (2010) compared the MCV with single-compartment vehicle (SCV), revealing the advantage of the former in simultaneous transport of different types of garbage separately from different locations to the collection centre. Specifically, they solved the classified garbage transport problem by such local search methods as 2-opt, crossover, swap and path redistribution, and contrasted the results with those of Fallahi [13]. Avella *et al.* (2004) assumed that the demand of each customer for certain products is inseparable, and that multiple vehicles can access the same customer to fulfil the demand of different products. To solve the CVRP in garbage collection network, Reed *et al.* (2014) [14] proposed an improved ant colony (AC) system with 2-opt local search, and solved the MCVRP in which each customer can be accessed only once by a vehicle. Gajpal and Abad (2009) created an AC algorithm to solve the VRP with simultaneous transmission [15]. Balseiro *et al.* (2011) combined the interpolation method with the AC algorithm to solve the VRP with time window constraints [16]. Based on the AC and tabu search, Cruz *et al.* (2013) proposed a sequential algorithm to solve the VRP problem with time window constraints, which transports various products with heterogeneous vehicles [17]. Valiček *et al.* (2017) and Tan *et al.* (2015) designed a heuristic algorithm which combines the AC system and 2-opt to tackle the VRP, and proved the algorithm as effective in solving the VRP and its deformation problem [18-19].

Inspired by Reed *et al.* (2014), the author extended the MCVRP using the multiple compartments of the vehicle. In the new problem, each vehicle transports various types of products in different compartments from the distribution centre (warehouse) to the customer. The constraints are as follows: all vehicles in the fleet are the same, each vehicle accesses to a specific group of customers, and each customer is accessed once only by each vehicle. For the minimal total travel distance, the existing FOA was enhanced by local search to assign customers rationally to a single path, and determine the order of these customers.

3. Materials and methods

3.1 Modelling of multi-compartment vehicle routing problem

In an actual logistics distribution network (Fig. 1), the MCVRP involves the following elements: a single distribution centre (warehouse), a fleet of MCVs, and several customers in need of distribution services. Note that each customer wants various products, the demand of each product is fixed, and each compartment has a fixed capacity. To fulfil the customer demand, each vehicle must leave from the distribution centre, access some customers and return to the centre. Each customer can only be accessed once by a vehicle. Given the distances between network vertices, the goal is to find the path of each vehicle that contributes to the minimum total travel distance. Table 1 lists the symbols associated with the mathematical model of the MCVRP and their meanings.

The undirected graph $G = (V, A, C)$ was employed to formally describe the distribution network of the MCVRP. Let $V = \{i | i = 0,1, \dots, n\}$ be the set of vertices in graph*,* with $i = 0$ being the distribution centre (warehouse), , in which the zero vertex is distribution $N = \{1, \dots, N\}$ be the set of customers served by k vehicles, and $A = \{(i, j) | i, j \in V\}$ the set of edges linking up the network vertices.

It is assumed that the vehicles are the same and located in the distribution centre (warehouse) at the beginning. Suppose each vehicle has p compartments, and p equals the number of products to be delivered. The number of product p demanded by customer I is denoted as q_{ip}.

For each customer, he/she should be accessed by a vehicle only once; for each vehicle, there should be a set of customers to be accessed in a strict sequence; for a given product, the total demand of the set of customers should not surpass the products to be deliver for customer i capacity Q_P of the compartments; for each path, the maximum length should not exceed L.

Table 1 Symbols associated with the MCVRP model and their meanings

Symbol	Meaning	Symbol	Meaning
V	The vertex of distribution network, including customers and distribution centres	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

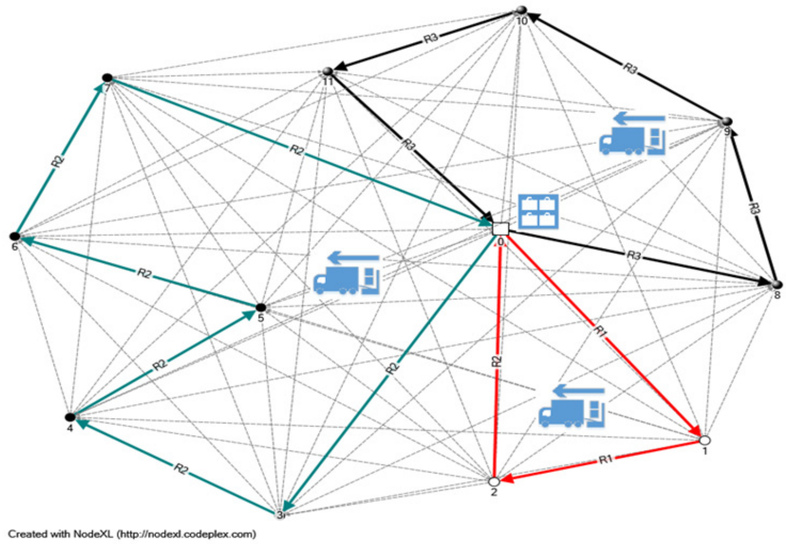

Fig. 1 MCVRP distribution network

Let $C = \{c_{ij} | (i,j) \in A\}$ be the distance matrix of network, where c_{ij} is the distance between customers i and j. The matrix is assumed to be symmetric, that is, $c_{ij} = c_{ji}$ .Let x_{ij}^k be a binary variable, which equals 1 if and only if vehicle k accesses customer j after accessing customer i Let Q_{ip}^k be the total delivery of product p after vehicle k leaves vertex i.

Hence, the MCVRP can be expressed as:

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

Min

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

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

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

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

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

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

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

Eq. 1 is the objective function that represents the total distance of all vehicles on all paths. Eq. 2 and Eq. 3 ensure that a path should pass through a vertex only once, that is, one vehicle can only access each customer once. Eq. 4 specifies that the path of each vehicle starts and ends at point 0 (warehouse). Eq. 5 and Eq. 6 eliminate the sub-loops and satisfy the capacity and connection demands between two customers. If $x_{ij}^{k} = 0$, Eq. 6 is not required as $Q_{ip}^{k} \le Q_p$ and $Q_{jp} \le Q_{jp}^{k}$. If $x_{ij}^{k} = 1$, Eq. 5 and Eq. 6 guarantee that $Q_{ip}^{k} - Q_{jp}^{k} \le -q_{jp}$, thus eliminating the sub-loops. Eq. 5 also stipulates that the total transport capacity falls within the vehicle capacity after the vehicle accesses vertex i, thus ensuring the capacity demand. Eq. 7 is the constraint of path length. Eq. 8 describes the variable x_{ij}^{k}, which equals 1 if and only if vehicle k accesses customer $j$after accessing customer i.

3.2 Hybrid fruit fly optimization algorithm

The FOA is a popular tool to find the optimal solution to NP-hard problems. It mimics the olfactory and visual functions of fruit flies in the foraging process. By this algorithm, the status of fruit flies is updated by searching the global optimum iteratively. In the course of iteration, once a fruit fly finds a better global optimum, all individuals in the population will gather to its location. The individual update mechanism lowers the population diversity, because the individual information is not shared or inherited, and adds to the risk of local optimum and premature convergence, as the position may not be the global optimum [20-21]. Zheng (2014) proposed a novel hybrid discrete algorithm for permutation flow scheduling problem. In the algorithm, the evolution of each generation consists of 4 phases: olfactory search, visual search, cooperative evolution and annealing [22]. Considering the strengths and weaknesses of the FOA, the author created a HFOA for the MCVRP.

Algorithm principle

Before updating path strength, the HFOA takes account of both the current best individual and the local optimum in the update of individual status. In this way, the algorithm ensures that the fruit flies concentrate towards the global optimum and inherits the local optimum information at the same time. The principle of the HFOA is illustrated in Fig. 2.

The HFOA is implemented in the following steps:

Step 1: Create the initial solution and initialize the path strength.
Step 2: Repeat the following operations until the termination condition.
Step 2.1: Create the path for m fruit flies.
Step 2.2: Perform local search to improve the solutions generated by each fruit fly.
Step 2.3: Update the best solution.
Step 2.4: Update the path strength for all edges against the best solution.
Step 3: Terminate the algorithm and record the best solution.

The HFOA uses fruit flies to construct path solutions to the MCVRP. In each iteration for path construction, each fruit fly performs four basic activities in turns. First, the fruit fly selects the next customer based on the probability function of path attraction, which consists of taste strength and path strength. Second, the fruit fly accesses the $Tabu$ list of customers in the current path. Third, the fruit fly updates the residual capacity of the compartment of the vehicle. Fourth, the fruit fly updates the path strength of edges which have been accessed. After that, the local search is introduced to improve the solution quality. Finally, the $Tabu$ list is deleted, marking the start of a new iteration. Table 2 shows the symbols of the HFOA and their meanings.

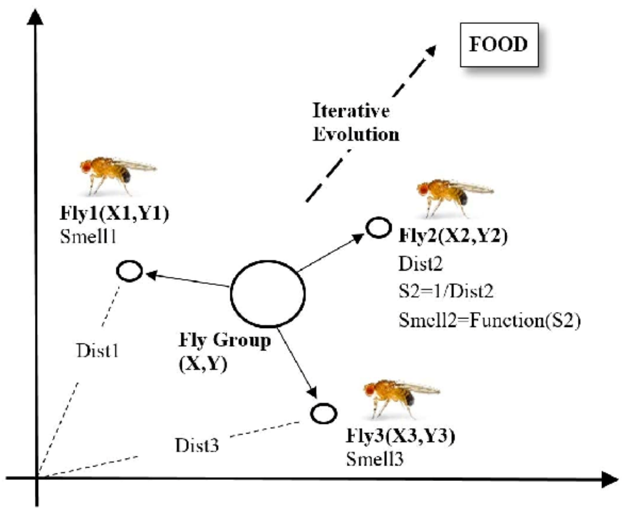

Fig. 2 Principle of the HFOA

Table 2 HFOA symbols and their meanings

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

Initialization

The first step of the HFOA is to generate the initial solution and initialize the strength of each path. The initial solution is generated in two steps. First, the customers are randomly generated according to the topological structure of the network; if the vehicle capacity is enough to meet customer demand, the customers are randomly added to the path of the vehicle; otherwise, the vehicle returns to the distribution centre (warehouse) before accessing the next customer. Fig. 3 is the flow chart of path initialization of the HFOA.

Path creation

Suppose each of the m fruit flies in the HFOA generates a complete path (a complete MCVRP solution). For solution diversify, each fruit fly should select the first customer randomly after leaving the distribution centre (warehouse). Next, each fruit fly should move to the subsequent customers based on the probability of path attraction (i.e. taste strength and path strength).

In the FOA, the taste strength is the reciprocal of the distance between the current location and the origin of the fruit fly. Here, the distance between the current location and the next customer is inversed as the taste strength. It is obvious that the strength is negatively correlated with the distance. Hence, the fruit flies tend to choose customers closer to the origin, laying the basis for minimizing the path length.

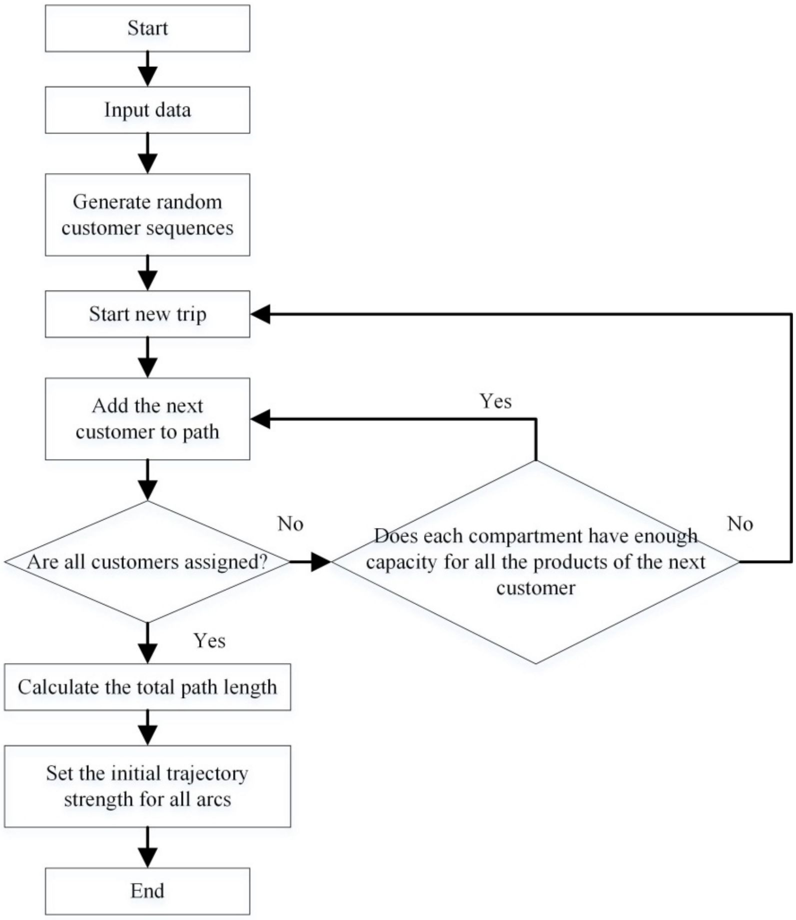

Fig. 3 Flow chart of path initialization in the HFOA

In light of the above, the attraction of edge ij consists of attraction power includes two parts: the path strength τ_{ij}, that is, the frequency of edge ij accessed during the iteration, and the taste strength μ_{ij}, that is, the reciprocal of the length of edge ij . The latter also represents the moving tendency of the fruit fly from i to j. Thus, the path attraction can be expressed as:

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

where α and β are the indices of path strength and taste strength, respectively. The probability that customer j will be accessed by the fruit fly after customer i is denoted as p_{ij} will be the next customer after the fruit fly visits the customer i:

$$p_{ij} = \begin{cases} \dfrac{\varepsilon_{ij}}{\sum_{l \in N_i} \varepsilon_{il}} & j \in N_i \\ 0 & \text{other} \end{cases} \tag{10}$$

where N_i is the list of all customers not yet accessed by the current vehicle, whose total demand does not exceed the vehicle capacity. According to Eq. 10, the choice probability of the next customer is proportional to the attraction of edge ij.

To accelerate the convergence, a threshold control mechanism was developed for customer selection. Before the fruit fly chooses the next customer j according to Eq. 10, a random variable q is generated such that it is evenly distributed in the interval of [0,1]. The next customer is selected according to Eq. 10 that is evenly distributed on the [0,1] is generated before each fruit fly chooses the next customer j according to the Eq. 10. If $q > q_0$; otherwise, the customer on the most attractive edge is selected. Hereinto, q_0 is a constant threshold indicating whether the next customer is determined according to Eq.10.

Next, each fruit fly continues to add customers in accordance with the above rules until no viable customer is left (N_i is empty). Then, the fruit fly goes back to the distribution centre and starts a new path. If the first customer on the new path is selected according to Eq. 10, then he/she must be the neighbouring vertex to the distribution centre. Thus, the customer search process becomes less diverse.

Local search

Since each trip of a fruit fly is a TSP (Lin, 1965) [23], the travel distance can be shortened by ensuring that the total demand on each path does not exceed the capacity limit. Hence, three local search operations were implemented after creating all the paths, aiming to enhance the solution quality, namely 2-opt, swap and insert:

- 2-opt: The path is divided at two points into three segments. Then, the customer sequence in the middle segment is inverted. After that, all the segments are linked up to reconstruct the path. Suppose that i and j are two non-adjacent customers on a path, and i^+ and j^+ are next adjacent vertices in the path, respectively. 2-opt means the creation of a new path by deleting edges (i, i^+) and $(j, j^+)$and adding edges (i, j) and (i^+, j^+). And (j, j^+), and adding and (i^+, j^+), so we get a new path.
- Swap: The locations of customers i and j in the current path set are switched to generate a new set of paths. Note that i and j may or may not fall onto the same path.
- Insert: Customer i is moved from location p_1 to location p_2 to generate a new set of feasible paths in the current path set. Note that $p_1$and p_2 may or may not fall onto the same path.

Through the above local search operations, the author obtained all feasible solutions and selected the shortest path from them.

Path strength update

In this step, the path strength of all edges is updated based on the optimal solution identified in the local search process. To simulate the actual situation, the path strength is assumed to decay with time.

The path strength is updated in two steps. First, the strength of all edges is reduced to reflect the decay intensity; second, the strength of the best path is increased to drive the fruit flies towards the shortest path. Let ρ be the path persistence coefficient$(0 \leq \rho < 1)$. Then, $1 - \rho$ discloses the path strength decay ratio during the iteration. Thus, the edge ij strength can be updated by the formula below:

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

where L^{best} is the total length of the best path in each iteration. The product of the path strength and ρ is the residual strength of the path after the decay. Then, the strength of the optimal path is updated by represents the residual strength of the trajectory after the decay, and then the adding $1/L^{best}$ to the residual decay intensity.

Fig. 4 presents the steps of the HFOA for the MCVRP.

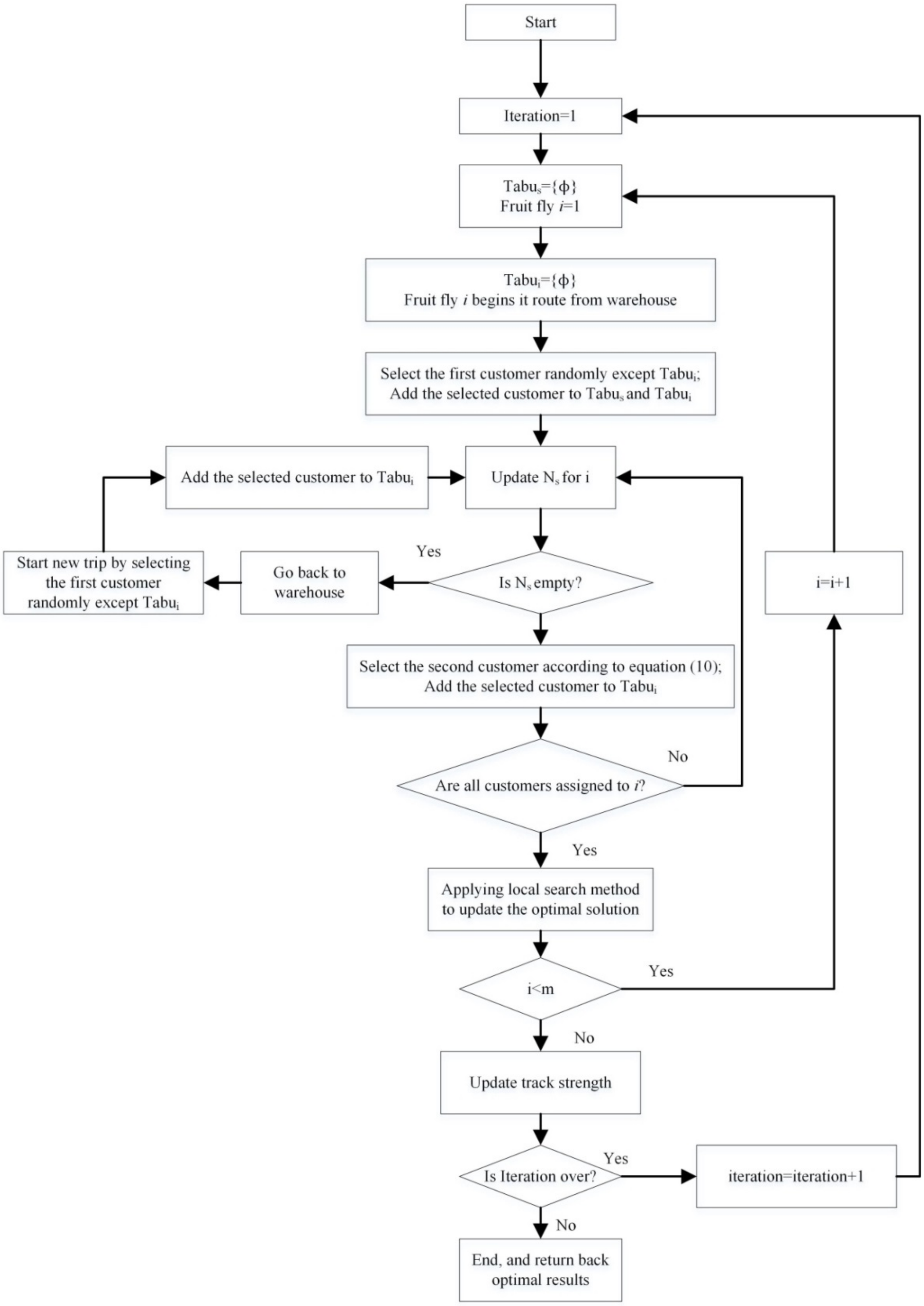

Fig. 4 Flow chart of HFOA for MCVRP

4. Results and discussion

4.1 Data and parameter settings

To validate the HFOA, the benchmark problem proposed by Laporte [24] was investigated, and the proposed algorithm was contrasted with the AC system [25-27] and hybrid ant colony (HAC) algorithm [28]. In view of the capacity constraint, 7 of 14 benchmark problems, denoted as VRPNC1-7, were selected for this research. The customers in VRPNC1-VRPNC5 obey random and even distribution, while those in VRPNC6-VRPNC7 obey aggregated distribution. These problems involve a total of 50-199 customers.

Suppose each vehicle has two compartments, whose capacity ratio is $1:3$. In other words, if the vehicle capacity is Q, then the capacity of the two compartments is $0.25Q$ and $0.75Q$, respectively.

The number of fruit flies in the HFOA, denoted as m, directly bears on both the best path quality and the computing time. After repeated tests, m was set to 20. The other parameters are as follows: Other parameters are: $\alpha = 1, \beta = 2, \rho = 0.9$ and $q_0 = 0.9$ .The experiment contains 100 iterations.

4.2 Effect analysis

In this section, the AC system, the HAC and the HFOA are simulated in Matlab. The simulation results, together with the improvement rate of the total path length, are recorded in Table 3.

As shown in Table 3, the average total length of the AC system, the HAC and the HFOA are respectively 1,053.977 unit length, 986.9929 unit length and 985.6029 unit length. Thus, the HAC improves the average total length by 6.36 % from that of the AC system, while the HFOA improves it by 6.49 % from that level. Thus, the HFOA has a similar effect to the HAC, and outperforms the AC system, indicating the advantage of heuristic algorithms in optimization operation. The slight edge of the HFOA over the HAC is attributed to the strong local search ability. In VRNPC6 and VRNPC7, the three algorithms differ very slightly in the total length. This is because customers are relatively clustered on these problems.

It is also observed that the total path length becomes better with the increase in the number of customers. The improvement rate shifts from 3.21 % at 50 customers to 9.83 % at 150 customers, indicating that the HFOA and the HAC are more effective when the problems are greater in size. Thus, the HFOA and the HAC are effective means to solve largescale problems, thanks to the local search operations. However, these operations need to consume a certain amount of time.

To verify its efficiency, the HFOA was applied to solve the benchmark problem VRNPC1. The results are displayed in Figure 5. It can be seen that the total path length is progressively shortened from 572.69 unit length, and converges to 551.27 unit length.

Table 3 Simulation results

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

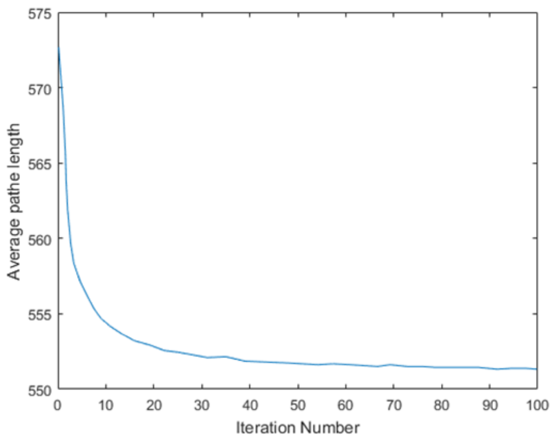

Fig. 5 The results of the HFOA on VRNPC1

4.3 Local search effect

To test the local search effect of HFOA, the three local search operations were implemented to the MCVRP in different combinations. Then, the results were compared with those of the FOA with no local search mechanism. The first combination integrates the FOA with the 2-opt operation, the second combination integrates the FOA with 2-opt and swap, and the third combination integrates the FOA with 2-opt, swap and insertion. Each combination has different number of iterations to achieve an equal computing time. According to the results in Table 4, the FOA with hybrid local search operations is good at shortening the optimal path length of the MCVRP (Fig. 6).

As shown in Table 4, the first combination enhances the solution quality by 11.86 %. However, the effect of the 2-opt operation is not good enough, as it only applies to a single trip. This operation does better in the TSP than the VRP. In the second combination, the solution quality is increased from 11.86 % to 13.04 %, indicating that the swap operation can move the customers on two paths. Finally, the third combination elevates the solution quality from 13.04% to 17.16 %, an evidence of the positive effect of hybrid local search on solution quality.

Table 4 Results of different combinations

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	985.60	17.16

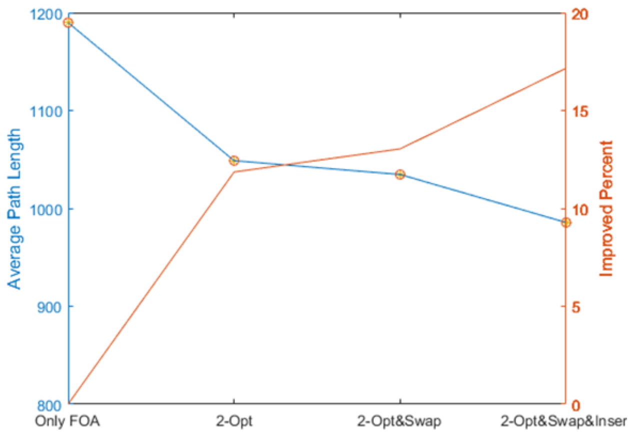

Fig. 6 Results of different combinations

4.4 Multi-compartment vehicle advantages

This section aims to disclose the advantages of the MCV. To do so, the Benchmark problem was solved by two modes. The first mode uses a SCV with the capacity of Q, while the second mode adopts a two-compartment vehicle. The capacity of the two compartments is respectively denoted as Q_1 and Q_2. The two vehicles have the same total capacity, i.e. $Q = Q_1 + Q_2$. Besides, there are two types of products, denoted as 1 and 2 respectively, to be delivered to the customer. Since the two products must be stored separately, a customer can be accessed twice on different paths to transport products 1 and 2. In this case, the VRP is decomposed into two sub-problems. The two sub-problems were solved separately, whose shortest paths were added up to get the result of the first mode. The results of the two modes on the 7 problems are shown in Table 5.

It can be seen from Table 5 that the total path length increases significantly when there is only one compartment. This is because a customer is visited twice to transport the two different products. The repeated visits increase the total travel distance. In the second mode, the two-compartment vehicle can serve more customers on each path than the SCV, thus reducing the total travel length. The advantage of the MCV is demonstrated by the 49.26 % shorter total length of the two-compartment vehicle than the SCV in Table 5.

Table 5 Results of the two modes on the 7 problems

Problem	Number of customer	Total length of vehicle with two compartment (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

5. Conclusion

The vehicle routing problem is a kind of NP-hard optimization problem with great research significance and wide application value in the intelligent logistics system. Aiming at the problem of vehicle routing optimization with capacity constraints in logistics distribution, a fruit fly optimization algorithm HFOA based on local search is proposed.

Local search operations are fundamental to solving combinatorial optimization problems. In this paper, three local search methods are combined with the FOA into a hybrid optimization algorithm to tackle the MCVRP. The effect of the proposed algorithm was verified with 7 benchmark problems. The numerical experiments show that the HFOA algorithm has improved the performance for all the problems, especially on largescale ones. The author also proved the necessity of the combination of local search and the FOA algorithm, and analysed the advantages of the MCV.

The simulation experiments on seven international benchmark problems show that the effectiveness and stability of the proposed algorithm HILS are compared with other algorithms in the literature. The overall performance of the algorithm HFOA is better. Of course, the HFOA only has a slight lead over the HAC in the total path of the MCVRP. The future research will seek to improve the combination of local search operations and the FOA.

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