Journal of Southeast University (English Edition) Vol. 31, No. 1, pp. 94 – 99 Mar. 2015 ISSN 1003—7985

Improved ant colony optimization for multi-depot heterogeneous vehicle routing problem with soft time windows

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Abstract: Considering that the vehicle routing problem (VRP) with many extended features is widely used in actual life, such as multi-depot, heterogeneous types of vehicles, customer service priority and time windows etc., a mathematical model for multi-depot heterogeneous vehicle routing problem with soft time windows (MDHVRPSTW) is established. An improved ant colony optimization (IACO) is proposed for solving this model. First, MDHVRPSTW is transferred into different groups according to the nearest principle, and then the initial route is constructed by the scanning algorithm (SA). Secondly, genetic operators are introduced, and crossover probability and mutation probability are adaptively adjusted in order to improve the global search ability of the algorithm. Moreover, the smooth mechanism is used to improve the performance of the ant colony optimization (ACO). Finally, the 3-opt strategy is used to improve the local search ability. The proposed IACO was tested on three new instances that were generated randomly. The experimental results show that IACO is superior to the other three existing algorithms in terms of convergence speed and solution quality. Thus, the proposed method is effective and feasible, and the proposed model is meaningful.

Key words: vehicle routing problem; soft time window; improved ant colony optimization; customer service priority; genetic algorithm

doi: 10.3969/j.issn.1003 – 7985.2015.01.016

The vehicle routing problem (VRP) has attracted much attention since it was first proposed by Dantzig and Ramser in 1959[1]. Multi-depot vehicle routing problem (MDVRP) is an extension of VRP and belongs to NP-hard problems. VRP with multiple expansion characteristics has been proposed in recent years[2–12]. Under actual conditions, heterogeneous vehicles are very common. Besides, traffic accidents, rush hour and other factors can affect the vehicle speed and the total cost, and the road conditions should be considered. Furthermore, considering customer service priority has become a development trend in logistics industry, in this paper, a multi-depot heterogeneous vehicle routing problem with soft time windows (MDHVRPSTW) is discussed due to its complexity and importance.

In recent years, many scholars have extensively researched MDVRP by heuristic algorithms and evolutionary algorithms. Rahimi-Vahed et al.[2] proposed a path link algorithm for the multi-depot periodic vehicle routing problem (MDPVRP). Ho et al.[3] developed two kinds of hybrid genetic algorithms (HGAs) to tackle the MDVRP. Tu et al.[4] introduced a bi-level Voronoi diagram-based metaheuristic algorithm to solve the large-scale MDVRP model. Yu et al.[5] developed an improved ant colony optimization (IACO) for a dynamic multi-depot vehicle routing problem(DMDVRP). Geetha et al.[6] proposed an improved k-means algorithm for clustering, using cluster first and route second for solving MDVRP, and the nested particle swarm optimization with genetic operators was used to solve each VRP. Mirabi et al.[7] developed three hybrid heuristics for solving MDVRP with uncertainty. Yu et al.[8] presented parallel improved ant colony optimization (PIACO) to solve MDVRP with a virtual central depot. Kuo et al.[9] proposed a variable neighborhood search for solving MDVRP with loading cost. Bettinelli et al.[10] presented a branch-and-cut-and-price algorithm for MDHVRPTW. Surekha et al.[11] grouped customers according to the nearest depot method first, and then used the C-W saving method to solve MDVRP. However, the above literature did not consider all of these factors. To solve the problem involving all factors, we propose a solution for MDHVRPSTW.

1 Problem Formulation

In this section, we formally state the MDHVRPSTW. The ultimate goal of the solution is to decrease the cost, in which customer demands are deterministic, and the locations of customers and depots are known. Different

Received 2014-06-12.

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Foundation items: The National Natural Science Foundation of China (No. 61074147), the Natural Science Foundation of Guangdong Province (No. S2011010005059), the Foundation of Enterprise-University-Research Institute Cooperation from Guangdong Province and Ministry of Education of China (No. 2012B091000171, 2011B090400460), the Science and Technology Program of Guangdong Province (No. 2012B050600028), the Science and Technology Program of Huadu District, Guangzhou (No. HD14ZD001).

Citation: Tang Yalian, Cai Yanguang, Yang Qijiang. Improved ant colony optimization for multi-depot heterogeneous vehicle routing problem with soft time windows[J]. Journal of Southeast University (English Edition), 2015, 31(1): 94 – 99. [doi: 10.3969/j.issn.1003 – 7985.2015.01.016]

depots have different kinds of vehicles that have various transportation costs, use-costs and loads. Moreover, speed is different at different times, but the driving time limit is set.

$$\min z = \sum_{i \in I \cup H} \sum_{j \in I \cup H} \sum_{v \in V} \sum_{h \in H} c_{ij} d_{ij} x_{ijk_v^h} + s_1 \sum_{i \in I} \max(e_i - T_i, 0) + s_2 \sum_{i \in I} \max(T_i - l_i + s_i, 0) + T_{\text{all}} w + \sum_{v \in V} \sum_{h \in H} c(k_v^h) n_v^h$$

$$t(i, j) = d_{ij} / v_{ij}$$

$$T_j = t(p(h), p(0)) + t(p(0), i) + w_i + s_i + t(i, j)$$

$$T_{\text{all}} = t(p(h), p(0)) + t(p(0), i) + \sum_{i \in I \cup H} \sum_{j \in I \cup H} t(i, j) + t(j, p(0)) + \sum_{i \in I} (w_i + s_i) \tag{1}$$

The following formulae are used to illuminate the constraints and definitions.

$$\sum_{v \in V} \sum_{h \in H} \sum_{j \in I \cup H} x_{ijk_v^h} = 1 \tag{2}$$

$$\sum_{i \in I} g_i y_{ik_v^h} \leqslant Q(k_v^h) \tag{3}$$

$$\sum_{i \in I \cup H} \sum_{j \in I \cup H} d_{ij} x_{ijk_v^h} \leqslant D_{\max} \tag{4}$$

$$\sum_{i \in I} \sum_{j \in H} x_{ijk_v^h} \leqslant 1 \tag{5}$$

$$\sum_{i \in I \cup H} x_{ijk_v^h} = \sum_{j \in I \cup H} x_{jik_v^h} \leqslant 1 \tag{6}$$

$$\text{eval}(X_z) = \max(T_r^h) \leqslant T_{\text{limit}} \tag{7}$$

$$T_e \leqslant T_{\text{start}}^{m_r^h} \leqslant T_l \tag{8}$$

$$\left.\begin{array}{ll} T_i < T_j & p_i < p_j \\ T_i > T_j & p_i > p_j \\ \text{Whatever} & p_i = p_j \end{array}\right\} \quad 0 \leqslant p_i \leqslant 3;\ i, j \in I;\ i \neq j;\ p_i \in \mathbf{N}^+ \tag{9}$$

The objective function can be expressed as Eq. (1), where I is the set of all customers; H is the set of all depots; i, j are one of the customers; V is the set of all types of vehicles; c_{ij} is unit fuel cost; d_{ij} is the distance between i and j, $i, j \in I \cup H$; $t(i, j)$ is the travel time from i to j, where v_{ij} is the vehicle speed. $x_{ijk_v^h}$ equals 1 when vehicle k_v^h finishes the task at customer i, then travels to j; $x_{ijk_v^h}$ equals 0, otherwise; s_1 is the waiting fee; s_2 is the late fee; T_i is the time of vehicle arriving in customer i; $[e_i, l_i]$ is the time window of i; s_i is the service time for customer i; T_{all} is the total time for finishing all tasks; w is drivers' salary in unit time; $c(k_v^h)$ is the use-cost of k_v^h; n_v^h is the number of k_v^h which is used in delivery; k_v^h is the vehicle type for depot h. Eq. (2) makes sure that each customer is assigned to a single route. Eq. (3) is the capacity constraint set for vehicles, where $y_{ik_v^h}$ equals 1, if k_v^h offer service for i; $y_{ik_v^h}$ equals 0, otherwise; g_i is the demand of customer i; $Q(k_v^h)$ is the capacity of vehicle k_v^h. Eq. (4) is the maximum route duration constraint, where $D_{\max}$ is mileage constraint. Eq. (5) assures that each customer can be served only once. Eq. (6) ensures that all delivery vehicles must return to the original depot after finishing the task. Eq. (7) is the longest running time limit, where eval (X_z) is the longest spend time by all used vehicles; T_r^h is the actual spend time for the vehicle k_v^h on route r; T_{limit} is the driving time limit. Eq. (8) is the actual departure time constraint, where $T_{\text{start}}^{m_r^h}$ is the actual departure time of vehicle; T_e and T_l are the pre-set earliest and latest departure time. Customer service priority is expressed as Eq. (9), where p_i is the customer service priority of customer i, $i \in I$, where $p(h)$ is the location of depots; $p(0)$ is the distribution center; $t(i, j)$ is the traveling time from i to j.

2 Improved Ant Colony Optimization

GA has rapid global search capability and can handle multiple groups of individuals. Multiple solutions of space searching are adopted to reduce the risk of falling into local optimal solutions. However, it does not make use of feedback information from the system, causing many unnecessary redundancy iterations and leading to low solving efficiency ultimately. While ACO converges to the optimal path through pheromone accumulation and updates, it has the characteristic of diversity and possesses a positive feedback mechanism.

However, it will cost too much time for accumulating the pheromone in the early search process, and then it will affect the solving speed. Combining the advantages of both the algorithms, and introducing other improved strategies, to construct a new improved ACO for MDHVRPSTW is our main task in this paper.

2.1 Initialization

SA was proposed by Gillett and Miller in 1994[12]. The idea of the algorithm is as follows: taking the distribution center as an origin and grouping customers by rotating the ray, until it cannot satisfy the constraint conditions, and then starting a new scan, until all the customers are scanned on the plane. The detailed steps are described below.

1) There are a number of depots and customers, and each customer must be assigned to one depot or route. Group customers according to the nearest principle.

2) Take the distribution center as the origin of the polar coordinates, and define the angle among depots and customers as 0. Then, transform the location of all customers into polar coordinates.

3) Group customers. Connect a customer and the depot, take the straight line as axis, and rotate the axis as the minimum angle between axis and other customers. Then establish a group, and add the customer into the group

gradually based on counterclockwise direction until the customer violates the constraints. Similarly, create a new group and add the rest of the customers into other groups.

4) Repeat steps 2) and 3) until all customers are grouped. Thus, a series of TSPs are formed.

2.2 Genetic algorithm

Integer encoding is used to encode the solution of the MDHVRPSTW. The fitness function is as follows:

$$f = 1/\min z \tag{10}$$

It is the reciprocal of the objective function. The parameters to be designed include population size P_{size}, maximum iterations G, crossover probability p_c, mutation probability p_m, and inversion probability p_{in}. Elite selection is a kind of basic guarantee for converging to the optimal solution. Part map crossover and single point mutation are to be adopted in the evolution process. Inversion operators can make the offspring inherit more parental information.

2.3 Ant colony optimization

2.3.1 State transition rules

The state transition rules are as follows:

$$P_{\phi\varphi}^{k} = \begin{cases} \dfrac{\tau_{\phi\varphi}^{\alpha}(t)\eta_{\phi\varphi}^{\beta}(t)}{\sum\limits_{s\in A_k}\tau_{\phi s}^{\alpha}(t)\eta_{\phi s}^{\beta}(t)} & \varphi \in A_k \\ 0 & \text{otherwise} \end{cases} \tag{11}$$

Each ant, denoted as ϕ, is assigned to a depot. The decision-making about combining customers is based on a probabilistic rule which takes into account both the visibility and the pheromone information on an edge. The ant uses the following equation to select the next customer φ, where $P_{\phi\varphi}^{k}$ is the choosing probability between ϕ and φ on the route; $\tau_{\phi\varphi}$ is the pheromone concentration on the edge (ϕ, φ); $\eta_{\phi\varphi}$ is the visibility on the edge $\tau_{\phi\varphi}$; α is the pheromone trail; β is the visibility value. A_k is the feasible customers' set.

$$s = \begin{cases} \arg\max\limits_{s\in A_k}[\tau_{\phi s}^{\alpha}(t)\eta_{\phi s}^{\beta}(t)] & \text{if } q \leqslant q_0 \\ S & \text{otherwise} \end{cases} \tag{12}$$

where q is a random number among $[0, 1]$; q_0 is a parameter, and $q_0 \in [0, 1]$. Combining deterministic selection and random selection can increase the probability of random selection. Moreover, it can also search the solution space more completely, thus overcoming the defects of ACO. The ant chooses the next customer according to the rule, or else chooses the edge as Eq. (11).

2.3.2 Updating pheromone information

The pheromone increments are assigned to each visited edge. The pheromone updating equations are as follows:

$$\tau_{\phi\varphi}(t+n) = \rho\tau_{\phi\varphi}(t) + (1-\rho)\Delta\tau_{\phi\varphi} \tag{13}$$

$$\Delta\tau_{\phi\varphi} = \sum_{\varphi\in J}\sum_{k\in k}\Delta\tau_{\phi\varphi}^{k\varphi} \tag{14}$$

$$\Delta\tau_{\phi\varphi}^{k\varphi}(t) = \begin{cases} Q/d_{\phi\varphi k} & (\phi, \varphi) \text{ is serviced by } k \\ 0 & \text{otherwise} \end{cases} \tag{15}$$

$$\rho(t) = \begin{cases} 0.95\rho(t-1) & 0.95\rho(t-1) \geqslant \rho_{\min} \\ \rho_{\min} & \text{otherwise} \end{cases} \tag{16}$$

where $\Delta\tau_{\phi\varphi}$ is the sum of pheromone increments on edge (ϕ, φ); $\Delta\tau_{\phi\varphi}^{k\varphi}$ is the pheromone increment on edge (ϕ, φ) on the k-th vehicle of the φ depot. The parameter that controls the speed of evaporation is denoted as ρ. It can improve the global search ability and lower the convergence speed by changing ρ adaptively, as shown in Eq. (16), and $\rho(t_0) = 1$.

2.3.3 Smooth mechanism

Smooth mechanism can improve the ability of exploration of new solutions by increasing the choice probability.

$$\tau_{\phi\varphi}^{*}(t) = \tau_{\phi\varphi}(t) + \delta[\tau_{\max}(t) - \tau_{\phi\varphi}(t)] \tag{17}$$

where $\delta \in (0, 1)$. The pheromone concentration is denoted as $\tau_{\phi\varphi}(t)$, and the pheromone track after smoothing is denoted as $\tau_{\phi\varphi}^{*}(t)$. When $\delta < 1$, the accumulated information is not lost completely in the process of the algorithm, and is only weakened; when $\delta = 1$, it means re-initialization of the pheromone track; when $\delta = 0$, the mechanism is closed.

2.4 Main improvement strategies for IACO

2.4.1 Adaptive crossover probability and mutation probability

The crossover operator and the mutation operator are introduced into IACO. The crossover operator can increase the optimization space and the mutation operator can restore the allele information. Moreover, mutation can improve the efficiency of the local search in large-scale population. However, changing p_c and p_m as individual units is a lack of team spirit, and this algorithm is not easy to escape from local optima in some cases, such as the stagnation of the overall evolution. Based on the above reasons, it is necessary to adjust the crossover probability and mutation probability adaptively, as shown in Eq. (18) and Eq. (19), where $p_c(t)$ and $p_m(t)$ are measured by average fitness f_{ave}, maximum fitness $f_{\max}$ and minimum fitness $f_{\min}$. The proximity of $f_{\max}$ and $f_{\min}$ reflects the concentration degree of the population.

$$p_c(t) = \begin{cases} p_c\dfrac{1}{1 - f_{\min}/f_{\max}} & \dfrac{f_{\text{ave}}}{f_{\max}} > a, \dfrac{f_{\min}}{f_{\max}} > b \\ p_c & \text{otherwise} \end{cases} \tag{18}$$

$$p_m(t) = \begin{cases} p_m\dfrac{1}{1 - f_{\min}/f_{\max}} & \dfrac{f_{\text{ave}}}{f_{\max}} > a, \dfrac{f_{\min}}{f_{\max}} > b \\ p_m & \text{otherwise} \end{cases} \tag{19}$$

2.4.2 3-opt strategy

The steps of the 3-opt strategy are as follows:

1) Remove three edges from the path and add three new edges in other parts, to form the full route. If the route length is shorter after the change, then maintain the results; otherwise, remove other edges and add new edges.

2) Repeat Step 1) until the quality of the solution cannot be improved. Then output the optimal solution, and exit the algorithm.

2.5 Algorithm process of IACO

The detailed steps are described below.

1) Group customers according to the nearest principle, and then construct the initial routes.

2) Design the GA parameters, and change crossover probability and mutation probability adaptively.

3) Generate the optimal solution if the conditions are satisfied, otherwise, turn to Step 1).

4) Generate the initial pheromone distribution according to the optimal solution, and design the ACO parameters. Put the ants at all nodes.

5) Calculate the probability that the ant moves to the next node. Each ant moves to the next node according to choice probability. Adjust α and β and update the route pheromone.

6) Iterate through all the points and increase the pheromone for the optimal ant circle.

7) The smooth mechanism is introduced, as shown in Eq. (17).

8) Adopt 3-opt local search to enhance the search ability for ACO, as described in Section 2.4.2.

9) If the termination conditions are satisfied, the maximum iteration number is reached or the same result is obtained, pause the run, and output the best solution; otherwise, turn to Step 5).

3 Experimental Results and Analysis

A remote traffic microwave sensor (RTMS) is installed to detect the average speed and traffic flow of eight lanes. According to the collected data, the relationship between time and speed is obtained by analysis and data integration and shown in Fig. 1.

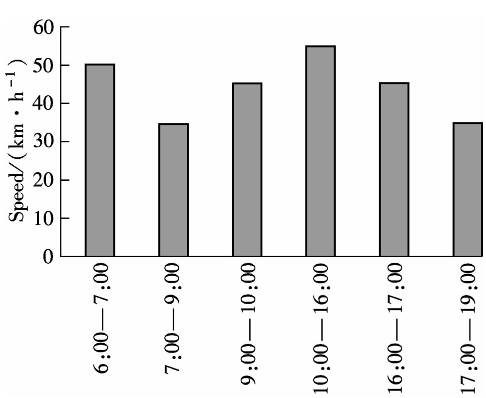

Fig. 1 Relationship between time and speed

In this section, a complex MDHVRPSTW mathematical model is set up. We performed some experiments on Microsoft Windows 7 operating systems (AMD A6-3420M 4 core CPU processor, 4 GB memory, 500 GB hard disk), using Matlab R2010b software, in order to evaluate the performance of the proposed algorithm. Then the performance of the algorithm was tested on three new data sets (32 customers, 50 customers and 80 customers), which were generated randomly.

Unlike the general MDVRP, the proposed MDHVRPSTW takes different types of vehicles, soft time windows, customer service priority, drivers' wage, etc. into consideration. The information of depots and customers is shown in Tabs. 1 and 2, respectively. There are three depots, the locations of which are (80, 10), (50, 80) and (20, 40), respectively. Also, there are 32 customers, sorted by 1 to 32, the demand of which are 2, 4, 8, 4, 4, 14, 8, 9, 6, 8, 5, 5, 4, 2, 8, 5, 2, 5, 1, 2, 4, 12, 10, 5, 11, 2, 12, 5, 2, 8, 1 and 1, respectively. In this paper, it is assumed that the earliest departure time is 6:00, and the latest departure time is 10:30. p_i = (1, 1, 3, 3, 3, 3, 2, 2, 1, 1, 3, 1, 3, 2, 3, 2, 1, 1, 2, 2, 1, 3, 3, 3, 3, 1, 2, 1, 2, 2, 3, 3) is customer service priority. The drivers' wage is 15 cost units, and the driving time limit is 300 time units. The maximum mileage constraint is 140 mileage units, and the service time is 6 min for every customer. The waiting fee and late fee are 10 cost units and 20 cost units, respectively.

Tab. 1 Information of depots

Depot	Types and number of vehicles	Load	Unit cost	Use cost
A	A1(2), A2(2)	35, 20	0.35, 0.20	10, 8
B	B1(1), B2(1), B3(1)	35, 20, 25	0.35, 0.20, 0.25	10, 8, 9
C	C1(1), C2(2)	25, 20	0.25, 0.20	9, 8

Tab. 2 Customers' information

Location	Time windows	Location	Time windows
(30,92)	[8:30, 9:00]	(56,49)	[8:20, 8:50]
(72,53)	[7:20, 7:50]	(40,60)	[7:00, 8:00]
(22,56)	[10:00, 10:30]	(60,60)	[9:10, 9:40]
(80,27)	[9:50, 10:20]	(35,24)	[9:10, 9:40]
(80,37)	[9:25, 9:45]	(72,59)	[7:00, 7:40]
(14,78)	[10:50, 11:10]	(29,47)	[9:00, 9:30]
(86,47)	[8:50, 9:20]	(48,62)	[9:30, 10:00]
(21,95)	[8:30, 9:00]	(58,62)	[9:30, 10:00]
(89,67)	[8:10 8:50]	(45,19)	[9:35, 10:00]
(18,92)	[8:00, 8:30]	(66,56)	[7:00, 7:30]
(50,3)	[10:00, 10:30]	(50,29)	[9:00, 9:30]
(44,55)	[6:40, 7:00]	(30,60)	[7:00, 7:30]
(66,10)	[9:50, 10:00]	(50,39)	[8:30, 8:50]
(70,70)	[9:00, 9:30]	(70,49)	[8:50, 9:30]
(90,17)	[10:00, 10:30]	(11,11)	[10:00, 10:30]
(34,88)	[8:40, 9:00]	(1,50)	[11:00, 11:30]

In order to verify the effectiveness of the adaptive strategy of GA, we take 32-customer data set as an example.

We give a comparison between GA and AGA (adaptive genetic algorithm), and the comparison is shown in Fig. 2. It shows that AGA is better than GA in solution quality and solving speed. At the same time, we design six parameters set for AACO (adaptive ant colony optimization). The results are shown in Fig. 3. We can see that the optimization effect is better when $\alpha=2, \beta=2, \rho_{\min}=0.6$. Thus, the parameters are set as follows: $P_{\text{size}}=30$, $G=300$, $q_0=0.88$, $Q=100$, $\alpha=2$, $\beta=2$, $\rho_{\min}=0.6$, $p_c=0.4$, $p_m=0.004$, $p_{in}=0.08$.

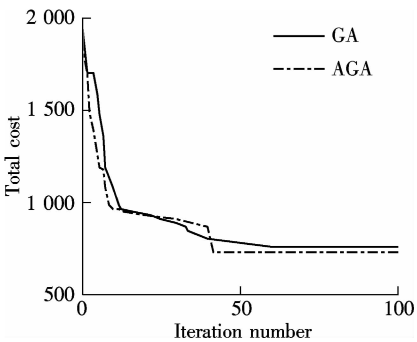

Fig. 2 Evolution curves of GA and AGA for MDHVRPSTW (32 customers, $p_c=0.4, p_m=0.004$)

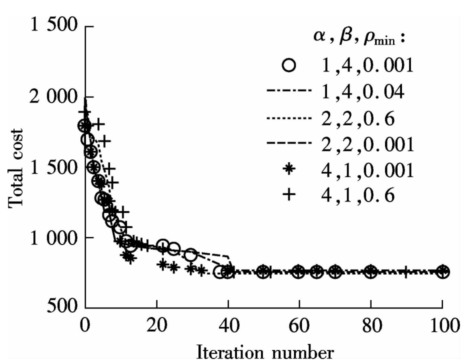

Fig. 3 Evolution curves of AACO for MDHVRPSTW (32 customers, $p_c=0.4, p_m=0.004$)

Tab. 3 shows the detailed information of distribution, and Fig. 4 shows the optimal route network of 32 customers.

Tab. 3 Experimental results of IACO for 32 customers

Routes	Time
A1→0→17→30→7→5→4→15→A1	6:00→7:00→8:23→8:52→9:20→9:38→9:56→10:17→10:35
A2→0→29→27→13→A2	7:00→8:16→8:40→9:02→9:40→10:02
A2→0→20→25→11→A2	7:00→8:16→9:12→9:32→10:00→10:39
B1→0→26→2→21→9→14→19→24→B1	6:00→6:36→7:01→7:27→7:42→8:20→8:58→9:22→9:31→10:02
B2→0→1→16→23→B2	6:30→7:08→8:33→8:48→9:44→10:13
B3→0→12→18→28→10→8→B3	6:00→6:36→6:50→7:03→7:25→8:28→8:40→9:36
C1→0→22→31→C1	8:00→8:54→9:27→10:18→10:56
C2→0→3→6→32→C2	9:00→9:42→10:17→10:48→11:24→11:52

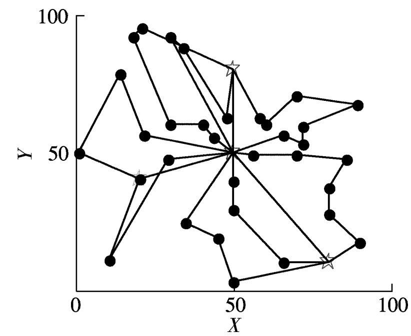

Fig. 4 The optimal route network of 32 customers

Four algorithms (IACO, GA in Ref. [11], PIACO in Ref. [8] and HGA2 in Ref. [3]) are applied to solve three new data sets. The comparisons of total delivery time and cost among four algorithms are shown in Fig. 5. IACO can converge to the best solution in the 20th generation, and the minimum cost is 716.8 cost units, as shown

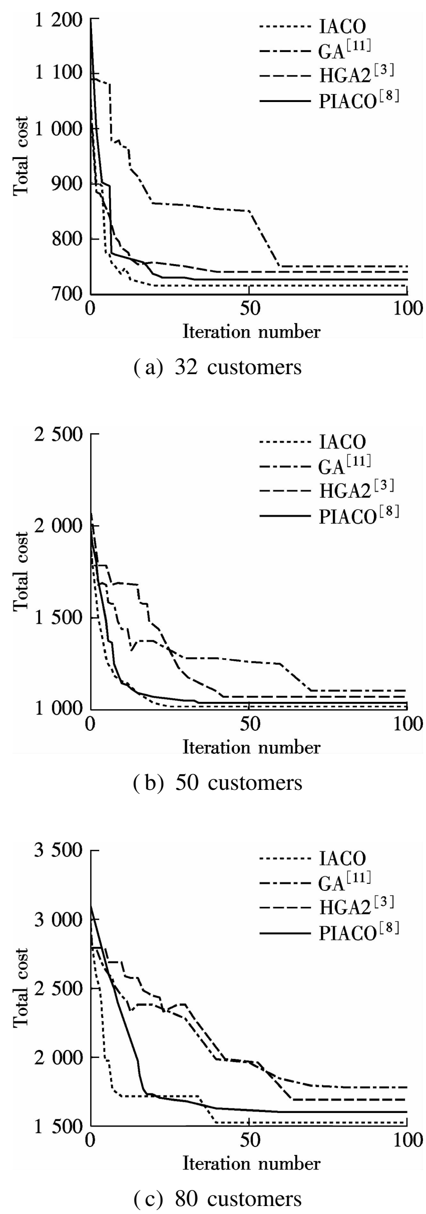

Fig. 5 Comparisons of total cost

in Fig. 5(a). It obtains the acceptable result of 750. 5 cost units in the 60th generation for GA, 726. 3 cost units in the 33th generation for PIACO and 738. 5 cost units in the 40th generation for HGA2. From Figs. 5(b) and (c), we can see that the proposed algorithm is better than GA, PIACO and HGA2.

Through the above description, we can obtain the conclusion that the proposed IACO can obtain more satisfying results compared with the other three algorithms. With the expansion of the problem, IACO can still obtain a better solution than the other three algorithms, although the convergence speed becomes slower. In a word, IACO obtains a satisfying solution and convergence efficiency. IACO is better than PIACO; HGA2 is better than GA but slightly worse than PIACO.

4 Conclusion

In this paper, an improved algorithm is proposed to solve MDHVRPSTW. First, genetic operators are introduced, and then crossover probability and mutation probability are adaptively adjusted to improve the global search ability of the algorithm. The smooth mechanism improves the performance of IACO. Moreover, the 3-opt strategy is used to improve the local search ability. This proposed algorithm provides a feasible method for MDHVRPSTW. To achieve a better intelligent algorithm for VRP with a variety of characteristics will be the future research direction.

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求解带软时间窗多车场多车型车辆路径问题的一种改进蚁群算法

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摘要:考虑实际生活中带多种扩展特征(如多车场、多车型、客户服务优先级、时间窗等)的车辆路径问题应用广泛,建立带软时间窗多车场多车型车辆路径问题的数学模型,并提出一种改进的蚁群优化算法(IACO)求解该模型. 首先,根据就近原则将客户分组,并通过扫描算法构造初始路径;其次,通过引入遗传算子并自适应地调整交叉概率和变异概率来提高算法的全局收敛能力,且采用平滑机制来提高蚁群优化算法的性能;最后,采用 3-opt 策略来提高算法的局部搜索能力. 将提出的算法应用在 3 个随机产生的实例中,仿真表明提出的 IACO 在收敛速度和解质量两方面都优于现有的 3 种算法,证明提出的算法是有效可行的,且提出的模型具有一定的实际意义.

关键词:车辆路径问题;软时间窗;改进蚁群优化算法;客户服务优先级;遗传算法
中图分类号:TP301