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Merged automobile parts maintenance delivery problem using an improved artificial bee colony algorithm

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Abstract. The merged automobile parts maintenance delivery problem has attracted interest from merged companies due to reduced delivery costs by collaborative delivery between several automobile part depots. Since the delivery problem is very complex, a Voronoi diagram is adopted to simplify it by splitting customers into several sets, and by attempting to solve it using the artificial bee colony algorithm. To improve the performance of the artificial bee colony algorithm, an adaptive strategy is used to control the proportion of scouts and leaders. Finally, the computational results for 23 benchmark problems indicate that the proposed algorithm is an effective method for solving multi-depot vehicle routing problems. Furthermore, the results of the merged automobile parts maintenance delivery problem also indicate that the improved artificial bee colony algorithm with the Voronoi diagram is feasible for solving this kind of delivery problem.

1. Introduction

During recent years, the automotive industry has become conceivably the largest growth industry in China. Commensurate with this growth are increasing demands for automobile maintenance parts, like lubricating oils, antifreeze, transmission fluids, coolants and so on, to assure the maintenance of automobiles after being sold. The increasing demands have caused many small suppliers for automobile parts maintenance to emerge. However, due to high oil prices, labor costs and fierce competition, many small money-losing automobile parts maintenance suppliers who cannot endure high operational costs will merge or go bankrupt. To find outlets for their survival, a company merger is one major method for solving this problem.

Since distribution costs have become a significant part of the operational costs of automobile parts maintenance suppliers, the term “merger”, especially in the same kinds of enterprise, has a positive effect on achieving economy of scale, debt offsetting or reduced business cyclicality. In the current situation, each supplier (depot) needs to serve these maintenance stations, respectively, to meet the requirements of automobile maintenance stations. Therefore, the merged company needs to consider how to serve the stations collaboratively from these depots to minimize the total travelling and vehicle operating costs of distribution [1]. Thus, this paper endeavors to solve the merged automobile parts maintenance delivery problem.

First, this paper seeks to describe the problem. There are several automobile parts maintenance depots to serve a set of automobile maintenance stations (customers), and thus the merged automobile parts maintenance delivery problem attempts to find a set of minimum cost routes to deliver the automobile maintenance parts from the automobile maintenance parts depots to a set of customers. In the merged automobile parts maintenance delivery problem, it is assumed that there are several depots to store the goods and deliver to a set of customers. Figure 1 describes the difference

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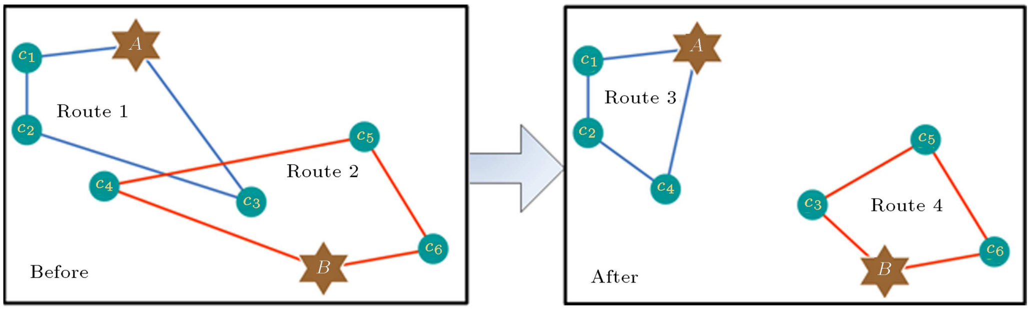


Figure 1. Comparison between the automobile maintenance delivery problems before and after company merger.

between the automobile maintenance delivery problem, before and after a company merger, based on a simple example.

In Figure 1, assume that there are two automobile maintenance depots (A and B), and six customers (c_1, c_2, c_3, c_4, c_5, c_6). Originally, company A is responsible for serving three customers (c_1, c_2, c_3), while company B is responsible for serving the other three customers (c_4, c_5, c_6). The delivery routes (routes 1 and 2) can be seen in Figure 1 (originally). When companies A and B are merged, the six customers are served by the two depots collaboratively. There may be new delivery routes (routes 3 and 4) acquired, which can be seen in Figure 1 (subsequently). From Figure 1, it is obvious that the length of route 3 + route 4 < route 1+ route 2. Therefore, the collaborative method can effectively reduce delivery costs. Thus, from a modeling viewpoint, the merged automobile parts maintenance delivery problem can be thought of as a Multi-Depot Vehicle Routing Problem (MDVRP).

The Multi-Depot Vehicle Routing Problem (MDVRP) is an extension of the vehicle routing problem and MDVRP is also a NP-hard problem. The heuristic algorithm is often the first choice for solving complicated problems [2-15], and recently, there have been many heuristic algorithms to solve MDVRP. Cornillier et al. [16] proposed a procedure based on a heuristic process to solve the multi-depot petrol station replenishment problem with time windows. Mirabi et al. [17] presented a hybrid heuristics for solving the multi-depot vehicle routing problem, using hybrid heuristics, constructive heuristic searches and improvement techniques to improve the performance of the algorithm. Dondo and Cerdá [18] attempted to solve the multi-depot vehicle routing problem using a time window with an improved algorithm. Yu et al. [19] aimed to solve the multi-depot vehicle routing problem using an improved ant colony optimization, where a coarse-grain parallel strategy, ant weight strategy and mutation operation are used to improve the searching ability of ant colony optimization. Ho et al. [20] attempted to solve the multi-depot routing problem with a hybrid genetic algorithm. The initial solutions of the algorithm are generated randomly in one hybrid genetic algorithm and the initialization procedure is performed in the other hybrid genetic algorithm. Tu et al. [21] proposed a Voronoi diagram-based metaheuristic to solve the multi-depot vehicle routing problem. Luo et al. [22] aimed to solve the multi-depot vehicle routing problem using a shuffled frog leaping algorithm in which a power law extremal optimization neighborhood search is used to rectify the positions for all frogs. Rahimi-vahed et al. [23] proposed a path relinking algorithm to solve a multi-depot periodic vehicle routing problem; in the problem, vehicles were considered homogeneous. Yu et al. [24] used ant colony optimization for solving a dynamic multi-depot vehicle routing problem, and an ant-weight strategy and mutation operation were presented to improve the performance of ant colony optimization.

The Artificial Bee Colony (ABC) algorithm simulates the process of bees looking for nectar, and has proven to be a generally applicable technique for optimizing real-world problems [25,26]. As a relatively novel heuristic algorithm, the ABC algorithm has achieved success in solving a series of complex combinational optimization algorithms. Szeto et al. [27] proposed an enhanced artificial bee colony to solve the capacitated vehicle routing problem. Özbakir et al. [28] successfully applied an artificial bee colony algorithm to solve generalized assignment problems with an ejection chain neighborhood mechanism. Liu and Liu [29] presented a hybrid discrete artificial bee colony algorithm to minimize the makespan in permutation flowshop scheduling problems. Koudil et al. [30] attempted to use an artificial bee colony algorithm to solve an integrated partitioning/scheduling problem in code sign. Other literature on the ABC algorithm can be found in [31,32,33]. These successful applications motivated us to apply the ABC algorithm to solve the merged automobile parts maintenance delivery problem in this paper.

Generally, the merged automobile parts maintenance delivery problem has been recognized as a MD-VRP, which is more complicated due to the embedded VRP. Thus, solving the merged automobile parts maintenance delivery problem to optimality is extremely time-consuming, and it is necessary to simplify it to attain optimization results in an acceptable time. There is a feasible way to change the merged automobile parts maintenance delivery problem into several one-depot merged automobile parts maintenance delivery problems, which can be thought of as VRPs. In this paper, the Voronoi diagram [34] is used to split customers into several sets by the depots. For each depot and its counterpart customer set, it may be considered as a sequence of VRPs. This can greatly reduce the computational complexity of the merged automobile parts maintenance delivery problem.

The focus of this paper is to solve a real-life delivery problem, the merged automobile parts maintenance delivery problem, which can be thought of as a Multi-Depot Vehicle Routing Problem (MDVRP) from a modeling viewpoint. Due to the complexity of automobile maintenance, the Voronoi diagram is used to simplify this problem, and then, ABC, a relatively new meta-heuristic, is applied to solve it. Thus, the remainder of this paper is organized as follows. In Section 2, we describe the merged automobile parts maintenance delivery problem and how the Voronoi diagram is used to simplify it. Section 3 presents the ABC algorithm and some improved strategies. Some computational results are discussed in Section 4, and lastly, conclusions are provided in Section 5.

2. Problem description

Currently, most suppliers of automobile maintenance in a certain area are independent operators. As an independent operator, the company tends to manage a privately-owned motorcade to deliver the products, although it is ineffective and unnecessary. It is obvious that the amalgamation of small or middle scale automobile maintenance companies would achieve economy of scale, debt offsetting and reduced business cyclicality. The model of the merged automobile parts maintenance delivery is proposed based on advantages that would come with enterprise merger, and it could be concluded that in the long run, the model would help in the long-term healthy growth of the industry of automobile maintenance.

2.1. The merged automobile parts maintenance delivery problem

The merged automobile parts maintenance delivery problem is described as follows: There are M automobile maintenance part depots, each of which owns K_i vehicles with the capacity of w $(i = 1, ..., M)$, and all of which are responsible for services for n customers; the demands of customers i are q_i $(i = 1, ..., n)$, and $q_i < w$. The distance between two customers or between customers and delivery points is described as the vertex set, C, which is partitioned into two subsets: $C_d = \{c_1, ..., c_H\}$ is the set of automobile parts maintenance depots, and $C_c = \{c_{H+1}, ..., c_{H+N}\}$ is the set of customers, respectively. The distance matrix is a real symmetric one, satisfying the triangle inequality principle, that is $c_{ik} \le c_{ij} + c_{jk}$. Each customer can be served by only one vehicle from any depot. Each vehicle can serve several customers whose demands must not overpass the transportation capacity of this vehicle. All vehicles start from one automobile parts maintenance depot, which it must return to.

Thus, the model of the merged automobile parts maintenance delivery problem is described as follows:

$$\text{Min} \sum\sum\sum\sum C_{ij} x_{ij}^{mk}, \tag{1}$$

$$s.t. \begin{cases} \sum_{k=1}^{K_m} \sum_{j=1}^{N} x_{ij}^{mk} \le K_m \quad \text{for} \\ \qquad i = m \in \{N+1+N+2, ..., N+M\} & \text{(1a)} \\ \sum_{j=1}^{N} x_{ij}^{mk} = \sum_{j=1}^{N} x_{ji}^{mk} \le 1 \quad \text{for} \\ \qquad i = m \in \{N+1, N+2, ..., N+M\}; \\ \qquad k \in \{1, 2, ..., k_m\} & \text{(1b)} \\ \sum_{j=1}^{N+M} \sum_{m=1}^{M} \sum_{k=1}^{K_m} x_{ij}^{mk} = 1 \quad \text{for} \\ \qquad i \in \{1, ..., N\} & \text{(1c)} \\ \sum_{j=1}^{N+M} \sum_{m=1}^{M} \sum_{k=1}^{K_m} x_{ij}^{mk} = 1 \quad \text{for} \\ \qquad j =\in \{1, ..., N\} & \text{(1d)} \\ \sum_{i=1}^{N} q_i \sum_{j=1}^{N+M} x_{ij}^{mk} \le q_{mk} \quad \text{for} \\ \qquad m \in \{N+1, N+2, ..., N+M\}; \\ \qquad k \in \{1, 2, ..., k_m\} & \text{(1e)} \\ \sum_{j=N+1}^{N+M} x_{ji}^{mk} = \sum_{j=N+1}^{N+M} x_{ij}^{mk} = 0 \quad \text{for} \\ \qquad i = m \in \{N+1, N+2, ..., N+M\}; \\ \qquad k \in \{1, 2, ..., k_m\} & \text{(1f)} \end{cases}$$

where:

$$x_{ij}^{mk} = \begin{cases} 1 & \text{the link from customer } i \text{ to } j \\ & \text{is visited by vehicle } k \text{ from depot } m \\ 0 & \text{otherwise} \end{cases}$$

C_{ij} in formula (1) stands for the costs from customer i to j; in this paper, it is the delivery distance from customer i to j; k is the number of vehicles; m is the number of automobile parts maintenance depots; q_{mk} is the capacity of vehicle k from depot m; K_m is the maximum number of vehicles at depot m; and k_m is vehicle k from depot m.

The objective of the merged automobile parts maintenance delivery problem is to minimize the total delivery distance or time spent in serving all customers, while meeting the following constraints: Constraint

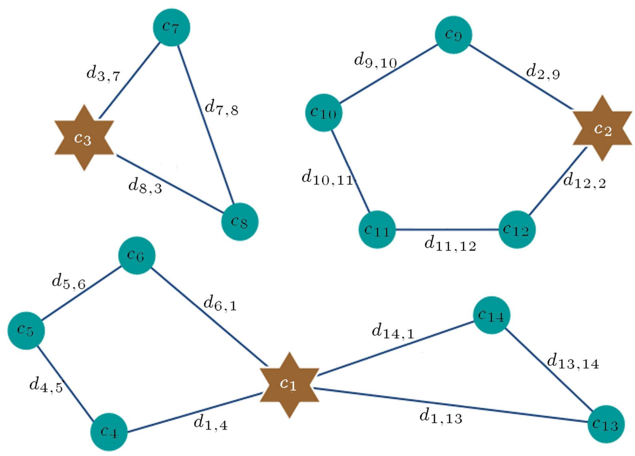


Figure 2. An example of the merged automobile maintenance part delivery problem.

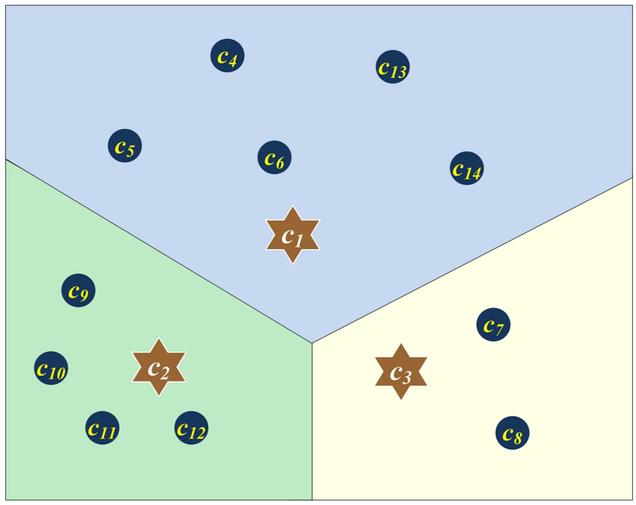


Figure 3. Voronoi diagram for simplifying the merged automobile maintenance part delivery problem.

(1a) ensures the maximum number of vehicles. Constraint (1b) makes sure that each vehicle starts and ends at the same depot. Constraint (1c) and (1d) assumes that each customer can be served exactly once by one vehicle. Constraint (1e) assumes that the quantity of goods in a vehicle cannot exceed its capacity. Constraint (1f) guarantees that there are no connections between these depots.

The merged automobile maintenance parts delivery problem can be described as in Figure 2. As shown, it is similar to a multi-depot vehicle routing problem. In the problem, the customers that are known in advance are represented by blue circles, while the brown stars represent depots. The objective of the merged automobile parts maintenance delivery problem is to find the least number of routes to deliver goods from several depots to these customers.

2.2. Simplification of merged automobile parts maintenance delivery problem with Voronoi diagrams

In the merged automobile parts maintenance delivery problem, the number of depots and customers is more complex than classical VRP, and thus, it is extremely time consuming for solving it to optimality. To simplify the problem efficiently, it is usual to divide the customers belonging to one depot and, thus, MDVRP becomes several VRPs.

The Voronoi diagram is a simple mathematical construction and one of the most important branches in computational geometry. A usual generic definition of the Voronoi diagram can be described as follows. Let S denote a set of n points (called sites) in the plane. The Voronoi cell $V(p)$ of p is the set of points that is closer (or equal) to p than to other sites of S.

The Voronoi diagram has been much studied in the past two decades by practitioners of computational geometry, and it has been proven useful in fields as diverse as associative file searching, cluster analysis, scheduling record accesses and collision detection [34]. Burge and Monagan [35] applied a Voronoi diagram to extract words and symbols from map images.

These successful applications of the Voronoi diagram motivate our use of it in simplifying the merged automobile parts maintenance delivery problem. An example of simplification is presented in Figure 3. As shown, there are three sites where the depots are used to split customers. Thus, the merged automobile parts maintenance delivery problem is partitioned into three Voronoi cells. Each Voronoi cell is then regarded as a VRP.

3. Improved artificial bee colony algorithm

3.1. The traditional artificial bee colony algorithm

The artificial bee colony algorithm is a new population-based metaheuristic approach which simulates the process of bees gathering honey [31]. The bee population is classified into three categories: scouts, leaders and onlookers. The searching activities of the ABC algorithm can be summed up as follows: When the leader finds a new food resource located in their neighborhood, they return to the hive to inform the onlookers by dancing. The onlookers will search for the new food resource in their neighborhood of the selected resource. Those leaders who have abandoned the food resource will become scouts and begin to look for a new food resource randomly.

In the ABC algorithm, each food resource position represents a possible solution of the optimization problem, and the amount of honey in each food resource corresponds to the fitness of each solution. Firstly, the ABC algorithm will produce SN original solutions randomly, which means SN honey bees and food resources. Each solution, named x_i $(i = 1, 2, ..., SN)$, is a D dimensional vector, and D is the number of optimization parameters. After initialization, the leaders begin to conduct a cyclical search for all the original solutions. During each search, every leader looks for a food source in the neighborhood and decides its fitness. If the fitness of the new food resource is better than the original food resource, the leader will replace the old one with it; otherwise, it will retain the old food source. When all the leaders have finished their searching tasks and return to the hive, they share the information of the food resources with onlookers. Onlookers select a food source according to its fitness. The probability, p_i, of selecting a food source, i, is determined by the following expression [7,34]:

$$p_i = \frac{f_i}{\sum_{n=1}^{SN}} f_n, \tag{2}$$

where, f_i is the fitness of the food resource position, $1 \leq i \leq SN$.

In order to produce a competitive food position compared with the old position, the ABC algorithm uses the following expression:

$$v_i = x_i + \Phi_i(x_i - x_k), \tag{3}$$

where, Φ_i is a parameter which is a random number in the range of [-1,1]. It can control the new solution falling in an acceptable range. Then, the fitness of the new solution is compared with the old. If the new fitness is better than the old, then, abandon the original food source and choose the new food source into the next iteration. If the new fitness is worse than the old, then, reserve the original food source.

If the food source cannot be improved after a limited number of cycles, it will be abandoned. The leaders of this food source will turn into scouts. The operation wherein scouts find a new food source and replace the original, x_i, is as follows:

$$x_i = x_{\min} + \text{rand}(0,1)(x_{\max} - x_{\min}). \tag{4}$$

The specific steps of the ABC algorithm are as follows:

Step 1. Generating the initial solution set, $i = 1, 2, ..., N$, $j \in (1, 2, ..., D)$.

Step 2. Calculating the fitness of each solution.

Step 3. The initial value of the external circulation, $m = 1$.

Step 4. The initial value of the internal circulation, $l = 1$.

Step 5. The leading bee searches for new solutions in the neighborhood based on Eq. (3) and calculates the fitness of the new solution.

Step 6. If the fitness of the new solution is better than that of the old, then the new solution replaces it, otherwise, the old solution will be retained.

Step 7. Calculating the fitness, then, probability p_i can be acquired based on Eq. (2).

Step 8. The following bees select food resource i (solution i), according to probability p_i, then search for new solutions in the neighborhood based on Eq. (2), and calculate the fitness of the new solution.

Step 9. Update the old solutions as that in Step 6, and then turn to Step 7.

Step 10. After all the bees finish the searching tasks, the best solution has been acquired.

Step 11. $l = l + 1$.

Step 12. $m = m + 1$.

Step 13. If $l < L$ (the maximum iteration in the internal circulation), then, turn to Step 5.

Step 14. After L iterations in the internal circulation, judge whether there is a solution to be abandoned or not. If true, a new solution, found by the scout based on Eq. (3), will replace the old.

Step 15. If $m < M$ (the maximum of times in the external circulation), then turn to Step 4.

3.2. Adaptive strategies

In the ABC algorithm, P_{Scout} is the ratio of scouts in the bee colony, which plays an important role in the search process of the ABC algorithm. If the value of P_{Scout} is higher, it will widen the search space of the ABC algorithm, but also take more computation time. P_{Leader} stands for the proportion of leading bees, which is also a significant parameter in controlling the convergence of the ABC algorithm. If the value of P_{Leader} is higher, it will enhance the search speed, but easily lead to local optimum.

Generally speaking, P_{Scout} with a larger value would lead to the ABC algorithm searching in a large space early in the iterations. In the later iterations, P_{Scout} with a smaller value would lead to the ABC algorithm carefully searching for new solutions in a small space. P_{Leader} with a smaller value would help the ABC algorithm exploit more search space in the early iterations. In the later iterations, P_{Leader} with a larger value would speed up the search for a new solution in the population. Thus, an adaptive strategy is proposed in this paper to improve the search ability of the ABC algorithm. This strategy ensures that P_{Scout} and P_{Leader} of the ABC algorithm can be adjusted, adaptively, with the searching process, based on the following formula:

$$P_{\text{Scout}} = P_{\text{Scout}}^0 - \sum_{k=1}^{N} \left[\frac{(f_{\max} - f)}{(f_{\max} - \overline{f})} \right]^{[(t \times 2)/N]+1}, \tag{5}$$

$$P_{\text{Leader}} = P^0_{\text{Leader}} + \sum_{k=1}^{N} \left[\frac{|f - \overline{f}|}{(f_{\max} - \overline{f})} \right]^{[(t\times 2)/N]+1}, \quad (6)$$

where, $f_{\max}$ and $\overline{f}$ represent the best fitness and the average fitness, respectively, f is the fitness of the current solution. The initial values of P_{Scout} and P_{Leader} are P^0_{Scout} and P^0_{Leader}, respectively. t stands for the number of the current iteration of the algorithm and N represents the maximum iteration of the algorithm.

4. Numerical analysis

This paper attempts to use an improved ABC to solve a real-life delivery problem, which is the merged automobile parts maintenance delivery problem. Since there are several depots in this delivery problem, for comparison, some well-known benchmark problems of MDVRP were applied to examine the feasibility and performance of the Improved ABC algorithm (IABC). Then, the IABC is used to solve the merged automobile parts maintenance delivery problem. The following will describe the two examples, respectively.

4.1. The classical MDVRP

In order to examine the performance of the proposed IABC in this paper, the benchmark problems of MDVRP from the literature [36-38] are selected. The main characteristics of these test problems are summarized in Table 1.

In this paper, VC++.NET 2003 is used to achieve the IABC, and the operating environment is a Pentium IV 2.93 GHz processor and 3 GB for the Windows platform. The large number of experiments to determine the parameters is as follows: The number of food sources is 50, the amount of population is 100 (half the bees are leaders and the remainder are onlookers), the maximum iteration is 1000, $P^0_{\text{Scout}} = 0.5$ and $P^0_{\text{Leader}} = 0.5$. In order to test the performance of the algorithm, the results of the proposed IABC algorithm are compared with the FIND algorithm [39], the CGL method [40] and PIACO [18]. These instances and the best known solutions are available at http://www.bernabe.dorronsoro.es/vrp/. Table 2 shows the results of these algorithms for solving the MDVRP.

Table 1. The information of the test problems.

No.	H	n	Q	No.	H	n	Q
1	4	50	80	13	2	80	60
2	4	50	160	14	2	80	60
3	5	75	140	15	4	160	60
4	2	100	100	16	4	160	60
5	2	100	200	17	4	160	60
6	3	100	100	18	6	240	60
7	4	100	100	19	6	240	60
8	2	249	500	20	6	240	60
9	3	249	500	21	9	360	60
10	4	249	500	22	9	360	60
11	5	249	500	23	9	360	60
12	2	80	60				

From Table 2, it can be found that most results of the IABC algorithm are close to well-known best solutions. Even several solutions are better than the best solutions among these algorithms. The results indicate that the IABC algorithm is suitable for solving MDVRP.

To evaluate the performance of the Voronoi diagram proposed in this paper, the computational results of the IABC without Voronoi (IABC-V) compared with IABC are shown in Table 3.

It can be observed from Table 3 that the solutions and computation times of the two algorithms are almost the same for solving some simple problems, such as test problems 1, 2, 3. However, with the larger number of depots or customers of the test problems, the computational results and times of the two algorithms are obviously different. Compared with the IABC-V, it can be seen that the Voronoi diagram can greatly reduce computation time. However, it also worsens the quality of the solutions. Based on the results in Table 3, it can be attained that the computation time can be reduced by 78%, respectively. At the same time, the quality of the solutions can be worsened by 1%, respectively.

Since, in a real-life delivery route problem, customers cannot wait for service for any length of time, the real-time feature in MDVRP is very important. Therefore, the computation time and quality of the solution should be considered simultaneously. To further validate the performance of the IABC, we add a bound in IABC and IABC-V, where each time step cannot exceed 200s of processing time. If the algorithm cannot complete its searching in the bound, the best solutions found in the 200s are noted in Table 4.

It can be observed from Table 4 that the solution quality of IABC-V obviously descends under the 200s constraint. This indicates that IABC-V is not suitable for a real-life multi-depot delivery route problem in a relatively smaller time constraint. Meanwhile, it can be observed that IABC can gain most optimum solutions. Therefore, this is expected that incorporation of the adaptive strategy for ABC and the Voronoi diagram can ensure better optimization.

4.2. The merged automobile parts maintenance delivery problem

The IABC algorithm is verified by the benchmark problem of the classical MDVRP, which shows that

Table 2. Computational results using IABC algorithm and some well-known published results.

No.	Best-known results	FIND [33]	CGL [34]	PIACO [18]	IABC
1	576.86	576.86	576.86	576.86	576.86
2	473.53	473.53	473.87	473.53	476.5
3	641.18	641.18	645.15	641.18	641.18
4	1001.49	1003.86	1006.66	1001.49	1020.52
5	750.26	750.26	753.4	750.26	750.26
6	876.5	876.5	877.84	876.5	878.34
7	885.69	892.58	891.95	885.69	891.95
8	4437.58	4485.08	4482.44	4482.38	4485.09
9	3900.13	3937.81	3920.85	3912.23	3937.82
10	3663.00	3669.38	3714.65	3663.00	3669.38
11	3554.08	3648.94	3580.84	3554.08	3648.95
12	1318.95	1318.95	1318.95	1318.95	1318.95
13	1318.95	1318.95	1318.95	1318.95	1318.95
14	1360.12	1365.68	1360.12	1365.68	1360.12
15	2505.29	2551.45	2534.13	2551.45	2579.25
16	2572.23	2572.23	2572.23	2572.23	2587.87
17	2708.99	2731.37	2720.23	2708.99	2731.37
18	3702.75	3781.03	3710.49	3781.03	3781.04
19	3827.06	3827.06	3827.06	3827.06	3827.06
20	4058.00	4097.06	4058.07	4097.06	4097.06
21	5474.74	5656.46	5535.99	5474.74	5656.47
22	5702.06	5718	5716.01	5772.23	5718
23	6095.36	6145.58	6139.73	6125.58	6145.58

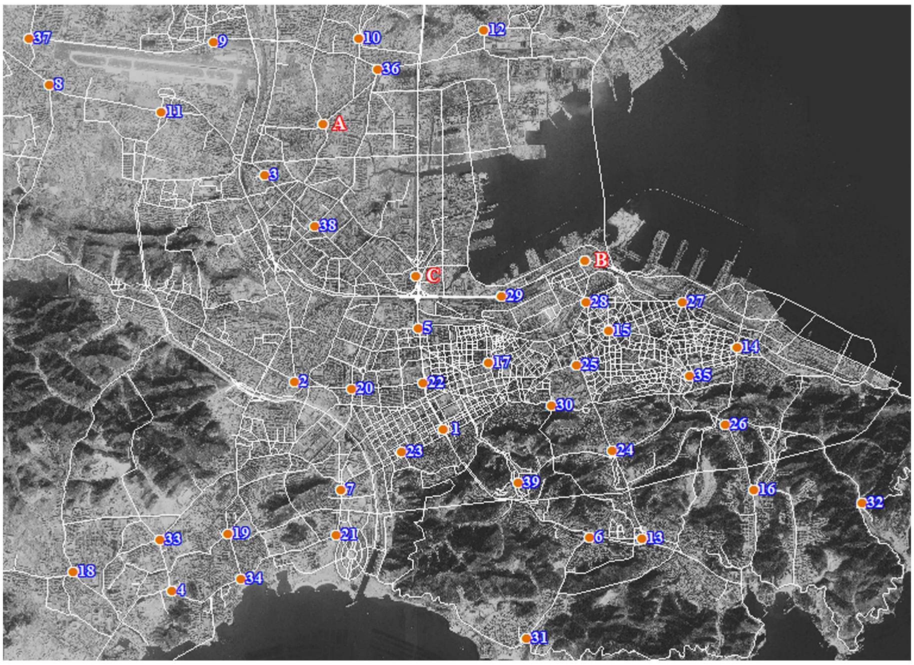


Figure 4. The location information of the merged automobile maintenance part delivery problem.

IABC is suitable for solving MDVRP. Then, a real-life problem is needed to be solved by the IABC algorithm. In the real-life routing problem, a road network is used to suggest the length of vehicle routing, and the least cost is the optimized objective of any network. Thus, vehicle capacity is 200 for a real-life delivery problem. Information regarding a real-life delivery route problem with the spatial characteristics of Dalian is described in Figure 4. Specific information of automobile parts maintenance depots and the automobile maintenance stations is shown in Tables 5 and 6, respectively. From Figure 4, there is a merged automobile parts

Table 3. Comparison results between IABC-V and IABC

No.	*H*	*n*	IABC-V		IABC	
			Length	Time	Length	Time
1	4	50	576.86	32	576.86	18
2	4	50	476.5	38	476.5	20
3	5	75	641.18	46	641.18	26
4	2	100	1006.66	89	1020.52	78
5	2	100	750.26	102	750.26	95
6	3	100	876.5	72	878.34	66
7	4	100	891.95	71	891.95	58
8	2	249	4482.44	498	4485.09	462
9	3	249	3937.82	362	3937.82	321
10	4	249	3663	298	3669.38	273
11	5	249	3580.84	235	3648.95	210
12	2	80	1318.95	96	1318.95	70
13	2	80	1318.95	84	1318.95	57
14	2	80	1360.12	91	1360.12	54
15	4	160	2551.45	120	2579.25	95
16	4	160	2587.87	160	2587.87	129
17	4	160	2731.37	155	2731.37	135
18	6	240	3781.04	188	3781.04	159
19	6	240	3827.06	193	3827.06	162
20	6	240	4097.06	213	4097.06	181
21	9	360	5656.74	452	5656.47	383
22	9	360	5716.01	390	5718	324
23	9	360	6145.58	322	6145.58	264
Avg	-	-	2694.6178	187.26	2699.94	158.26

maintenance delivery problem, where there are several automobile maintenance parts depots and some maintenance stations in Dalian city. The problem is how to send the automobile maintenance parts to the maintenance stations with the least delivery cost.

As shown in Figure 4, the letters (A, B and C) stand for three automobile maintenance parts depots in Dalian, and the numbers (1, 2,..., 39) represents the thirty-nine automobile maintenance stations in Dalian.

4.2.1. The process of distance matrix construction based on road networks

As is the case in practice, the distance traveled by vehicles should be measured based on the road network. Thus, a method is adopted to measure actual distance and transfer it to the distance matrix. Figure 5(a) describes the "initial" scenario of an example with three points on the route network. There are three points selected: point A, point 3, and point 38, and we attempt to acquire the distance matrix based on a real road network. The following will describe the process of how to transfer the actual route distances into rectilinear distances.

Table 4. Comparison results between IABC-V and IABC in the time constraint (200s).

No.	*H*	*n*	IABC-V		IABC	
			Length	Time	Length	Time
1	4	50	576.86	32	576.86	18
2	4	50	476.5	38	476.5	20
3	5	75	641.18	46	641.18	26
4	2	100	1020.52	89	1020.52	78
5	2	100	750.26	102	750.26	95
6	3	100	876.5	72	878.34	66
7	4	100	891.95	71	891.95	58
8	2	249	5571.2	200	4511.6	200
9	3	249	6122.4	200	4284.62	200
10	4	249	5987.6	200	3815.6	200
11	5	249	6058.9	200	3733	200
12	2	80	1318.95	96	1318.95	70
13	2	80	1318.95	84	1318.95	57
14	2	80	1360.12	91	1360.12	54
15	4	160	3092.99	120	2579.25	95
16	4	160	3299.43	160	2587.87	129
17	4	160	3310.4	155	2731.37	135
18	6	240	5012.7	188	3781.04	159
19	6	240	5034.9	193	3827.06	162
20	6	240	5443.21	200	4097.06	181
21	9	360	6712.24	200	5791.5	200
22	9	360	6533.14	200	5857.3	200
23	9	360	7465.3	200	6494.6	200
Avg	-	-	3429.4	136.39	2753.28	121.87

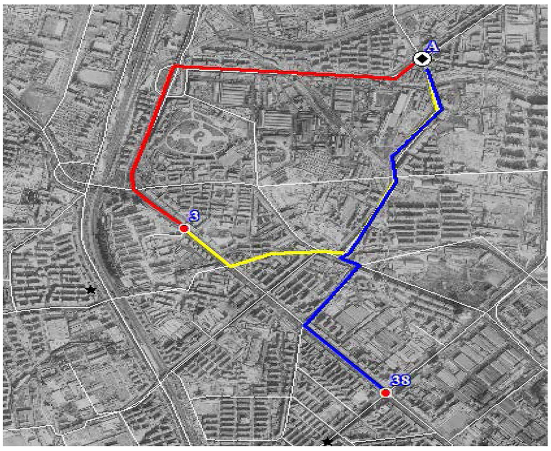
Table 5. The information of automobile part suppliers.

Depots	A	B	C
Longitude	121.578	121.637	121.6
Latitude	38.959	38.9337	38.932
Vehicle number	3	3	3

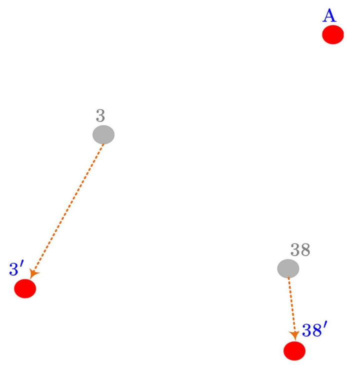
Firstly, the route distance between two points should be calculated. For example, if there are two routes from point A to point 3, to calculate these distances, the shortest route length is considered the route length between point A and point 3 (Figure 5(b) shows the road routes between these two points). If there are two routes (red and yellow lines, respectively) between point A and point 3, it is necessary to determine the true routes first. Since the length of the yellow line between point A and point 3 is less than that of the red line, the length of the yellow line is considered the route length between point A and point 3.

Secondly, based on the route length between point A and point 3, the rectilinear distance between them can be attained by moving point 3 to point 3′. While

(a) The locations of three customers



(b) Selecting the vehicle route between two customers



(c) The conversion of the actual route length between two points

Figure 5. The construction of the distance matrix based on road network.

meeting, the rectilinear distance between point A and point 3′ is equal to the actual route length between point A and point B (see Figure 5(c)). Thus, the rectilinear distance between point A and point 3′ can represent the route length between point A and point 3. In the same way, the rectilinear distance between point A and point 38′ can represent the route length between point A and point 38 (see Figure 5(c)). Therefore, the distance matrix based on a real road network can be attained based on this method.

Thirdly, when point 3′ represents point 3, one should measure the rectilinear distance between point A and point 3′, and when point 38′ represents point 38, one should measure the rectilinear distance between point A and point 38′. In the same way, the rectilinear distance between lots of points based on real road networks can be attained correspondingly. Figure 5 shows the process of the method to transfer actual distance into a symmetric distance matrix.

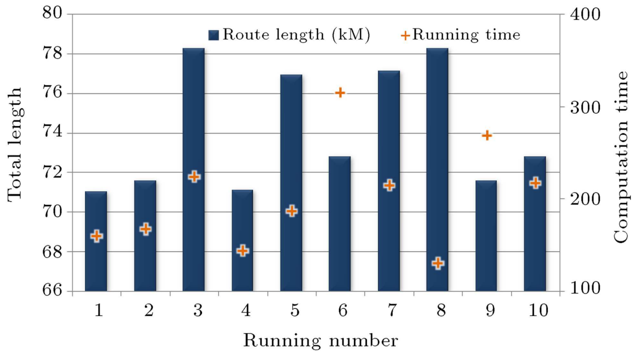


Figure 6. Computing the results of IABC after running 10 times.

4.2.2. The computational results of a real-life merged automobile parts maintenance delivery problem

The IABC will continue calculating 10 times, and the results are shown in Figure 6. We can see that the results are very stable, and the difference between the optimum and the worst plan is less than 10%, which shows that this algorithm has excellent convergence performance. Meanwhile, the computing time, from 130 to 320 seconds, is relatively short for a real-life problem. An understanding of the optimization quality and computing time of this algorithm shows that the proposed IABC can solve the automobile maintenance parts supply delivery problem in optimizing delivery routes for automobile maintenance part supply services to maintenance stations in Dalian city. The length of the routes is 70.97 kM and the optimized routes are shown in Figure 7.

From Figure 7, it can be observed that the optimization results of the distribution routes can result in more customers and the positions of customers seem to be highly concentrated. This is because the automobile maintenance parts delivery formulation can assign tasks collaboratively to acquire the least delivery routes. The results also prove that the automobile maintenance parts delivery formulation is feasible and the improved ABC is an effective measure to optimize the merged automobile parts maintenance delivery problem.

To examine the effectiveness of the proposed method in this paper, the solution of the current

Table 6. The information of the automobile maintenance stations in Dalian.

Customers	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Longitude	38.9072	38.9118	38.9489	38.876	38.9224	38.884	38.8939	38.9679
Latitude	121.608	121.574	121.567	121.548	121.601	121.639	121.584	121.519
Demand	10	24	20	12	10	12	10	38
Customers	**9**	**10**	**11**	**12**	**13**	**14**	**15**	**16**
Longitude	38.9742	38.9796	38.9633	38.9758	38.8846	38.9184	38.9212	38.8919
Latitude	121.557	121.587	121.546	121.612	121.651	121.674	121.642	121.676
Demand	18	80	50	50	24	36	20	30
Customers	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**
Longitude	38.9156	38.8772	38.8846	38.9109	38.885	38.9124	38.9008	38.8987
Latitude	121.616	121.527	121.56	121.587	121.584	121.601	121.599	121.644
Demand	16	18	16	18	22	10	15	15
Customers	**25**	**26**	**27**	**28**	**29**	**30**	**31**	**32**
Longitude	38.9149	38.9055	38.9263	38.9264	38.9276	38.9089	38.8646	38.8872
Latitude	121.636	121.666	121.658	121.638	121.619	121.63	121.626	121.7
Demand	15	60	30	20	28	20	16	18
Customers	**33**	**34**	**35**	**36**	**37**	**38**	**39**	
Longitude	38.8837	38.8766	38.9148	38.9687	38.9755	38.9404	38.8936	
Latitude	121.546	121.564	121.66	121.59	121.513	121.577	121.623	
Demand	20	13	20	60	22	40	10	

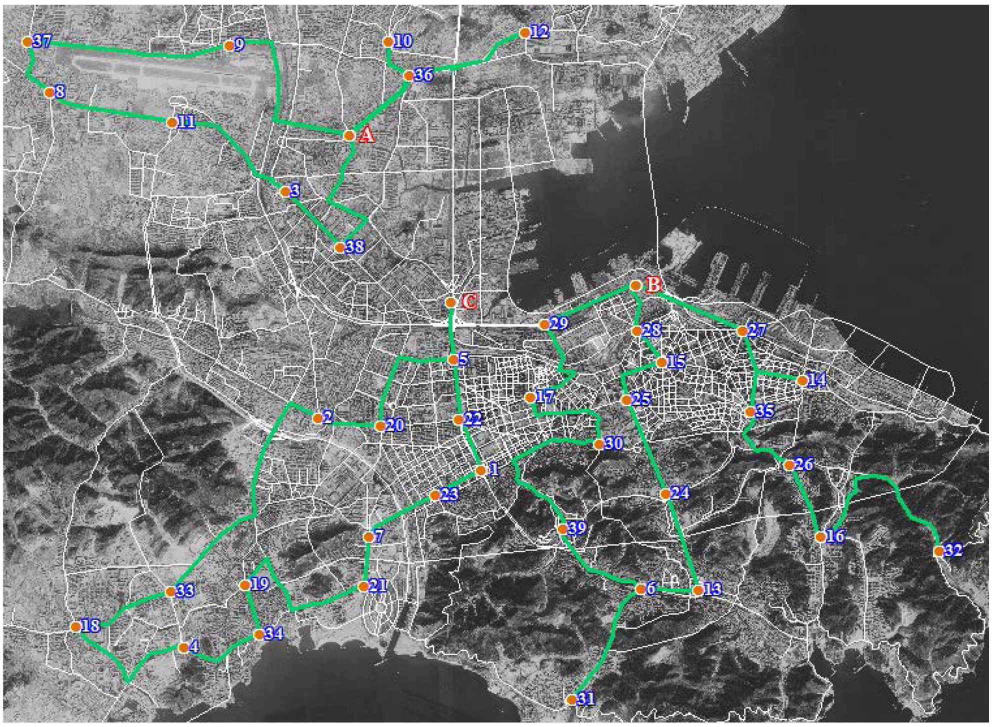


Figure 7. Distribution routes of the merged automobile maintenance part delivery problem based on ABC.

situation (before company merger) is compared with the optimized solution of the proposed method, which can be seen in Table 7.

From Table 7, it can be found that the total distance from the current situation is obviously longer than that of the proposed model. This is because the proposed delivery routing model can provide a new way for solving the delivery problem simultaneously, which can greatly shorten delivery routes and complete deliveries. Furthermore, the number of vehicles is

Table 7. The number of vehicles and the total distance between the current situation and the proposed method.

	The number of vehicle	Total distance (kM)
The current situation	9	132.13
The proposed method	4	70.97

obviously less than that of the current situation. This is because, in the current situation, each company needs to serve its customers, respectively. In this situation, to meet customer demands, each vehicle is often with a partly empty container, which greatly wastes the fixed costs of retaining vehicles. Therefore, our proposed method is effective and the improved ABC is an effective method to solve the merged automobile parts maintenance delivery problem.

5. Discussion and conclusion

The results show that the merged automobile parts maintenance delivery problem proposed in this paper can effectively integrate with several smaller companies to keep their competitiveness in the market by reducing delivery costs. As expected, the use of the Voronoi diagram and the improved artificial bee colony algorithm could effectively reduce the complexity and increase the application availability of large scale MDVRP, especially the MDVRP problem that requires a fast solution. However, the model can effectively reduce delivery costs after company merger. It will also bring some problems, like profit assignment, between these sub-companies. Moreover, the transportation cost only corresponds to transportation distance. In fact, under real-life conditions, transportation costs would be related to traffic conditions (time-of-day, weather and so on). Further study may consider other aspects of real-life problems, in order to enhance the performance of the proposed methods.

Therefore, the objective of the merged automobile parts maintenance delivery problem is to minimize total delivery distance in serving all maintenance stations in the city. Since the merged automobile parts maintenance delivery problem is difficult to solve, in this paper, the Voronoi diagram is firstly used to split maintenance stations into several sets using automobile maintenance parts depots. Then, an ABC is presented to solve the multi-depot automobile parts maintenance supply delivery problem. To improve the performance, an adaptive method is used. The computational results of the benchmark problems suggest that the proposed adaptive ABC is effective for solving MDVRP. Implementation of the multi-depot automobile parts maintenance supply delivery problem, in the design of delivery routes for several automobile parts maintenance depots to serve some service stations in Dalian, can provide suitable results. Therefore, the proposed adaptive ABC can be considered an effective method for the merged automobile parts maintenance delivery problem.

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