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The application of tabu search algorithm on split delivery open vehicle routing problem

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ABSTRACT

The traditional Open Vehicle Routing Problem (OVRP) assumes that the client's demand can not be split and the type of vehicles is the same, but in the practical logistics distribution, the type of vehicles is not exactly the same, sometimes the transportation cost can be reduced by splitting the demand of clients to make the best of the loading capacity of vehicles. This paper proposes the Split Delivery Open Vehicle Routing Problem with Heterogeneous Vehicles (SDOVRPHV) presents mathematic model with the integer programming, solves the problem with Tabu search algorithm and improves the generation of initial solution and neighborhood structure in the algorithm, By experiments, the effectiveness of model is validated, and the results are compared with the traditional OVRP which indicates that the algorithm can reduce effectively the transportation cost.

KEYWORDS

Tabu search algorithm;
Open vehicle routing problem (OVRP);
Split delivery;
Vehicle routing problem (VRP).

INTRODUCTION

Open Vehicle Routing Problem (OVRP) in the reality has a wide range of applications, the current OVRP researches mainly have: the literature[1] gives some suggestions to improve the CW saving algorithm. Literature[2] puts forward some tabu search algorithms to solve OVRP with capacity and path length constraint. Literature[3] puts forward an intelligent optimization algorithm with method of threshold acception, under the guidance of threshold value T to search solution space, in order to get the best solution structure under the constraint conditions. Literature[4] puts forward accurate algorithm to solve this type of problem, this is an accurate algorithm based on a branch section method. Literature[5] puts forward a forward greedy algorithm to solve OVRP with time windows. Literature[6] presents a genetic algorithm to solve open vehicle routing problem by loading capacity constraint.

In the traditional OVRP, the clients' demand can not be split, vehicle type is the same, this can cause the vehicle's empty loading rate higher, resulting in waste of vehicle resources, and therefore, solving the vehicle routing problem with split delivery has better practical significance. This paper presents a kind of Split Delivery Open Vehicle Routing Problem with Heterogeneous Vehicles (SDOVRPHV) to establish an integer programming model of this problem, design a tabu search algorithm to solve the problem, compares and analyzes the results.

DESCRIPTION OF SDOVRPHV PROBLEM

Explaining research chronological, including research design, research procedure (in the form of algorithms, Pseudocode or other), how to test and data acquisition[1,3]. The description of the course of research should be supported references, so the explanation can be accepted scientifically[2,4].

SDOVRPHV is an extension of OVRP, it refers to a group of different type of vehicles starting from the depot to visit each client with known demand, when visiting a client, client's demand is not necessarily completed by one truck, but also by many trucks to complete together, that is, multiple trucks can split the clients need to complete a client demand service together, finally don't return back to the original depot. Because of flexible condition that client's demand can be split and different kinds of vehicles are provided, vehicle's full load can be largely realized, loading capacity can be fully utilized. Therefore SDOVRPHV is with minimal cost of vehicles, the largest use of vehicle loading capacity and minimum driving distance cost to meet the needs of all clients to determine the vehicle route. Among them, minimizing the cost of vehicles is the first goal, maximizing vehicle loading ability is the second goal, and minimizing the cost of vehicle traveling distance is the third goal.

For convenience, supposing the split delivery is an integer's split, the number of depot is 0, the client's numbers are *l*, 2, ..., *N*. The variables are defined as follows:

$$x_{ijv} = \begin{cases} 1 & \text{represents vehicle } v \text{ from client } i \text{ to client } j \\ 0 & \text{otherwise} \end{cases}$$

$$z_v = \begin{cases} 1 & \text{vehicle } v \text{ is used} \\ 0 & \text{otherwise} \end{cases}$$

q_i^v represents the distribution quantity of vehicle v from the client i. Then the integer mathematical programming model can be described as:

$$\min\left(\sum_{v=1}^{V} \eta_v z_v C_v + \sum_{v=1}^{V} \lambda_v (z_v C_v - \sum_{I=1}^{N} q_i^v) + \sum_{v=1}^{V}\sum_{i=0}^{N}\sum_{j=1}^{N} u_v l_{ij} x_{ijv} \right) \quad \mathbf{(1)}$$

$$\sum_{i=1}^{N} x_{0iv} = 1 \qquad \forall v \qquad \mathbf{(2)}$$

$$\sum_{i=1}^{N} x_{i0v} = 0 \qquad \forall v \qquad \mathbf{(3)}$$

$$\sum_{i=0}^{N}\sum_{v=1}^{V} x_{ijv} \geq 1 \qquad \forall j > 0, i \neq j \qquad \mathbf{(4)}$$

$$\sum_{j=1}^{N}\sum_{v=1}^{V} x_{ijv} \geq 1 \qquad \forall i,\ i \neq j \qquad \mathbf{(5)}$$

$$\sum_{i=1}^{N} x_{ijv} = \sum_{k=1}^{N} x_{jkv} \qquad \forall j>0, \forall v \qquad \mathbf{(6)}$$

$$\sum_{v=1}^{N} q_i^v = \mathrm{d}_i \qquad \forall i>0 \qquad \mathbf{(7)}$$

$$\sum_{v=1}^{N} q_i^v \leq \mathrm{C}_v \qquad \forall v \qquad \mathbf{(8)}$$

$$\sum_{v=1}^{N} \mathrm{C}_v \leq \sum_{i=1}^{N} d_i + \mathrm{C}_m \qquad \mathbf{(9)}$$

$$q^v > 0, q_i^v = 1, 2, ..., C_v, v = 1, 2, ..., V \qquad \mathbf{(10)}$$

$$z_v = 1 - x_{ijv} \qquad \forall v \qquad \mathbf{(11)}$$

$$z_v \geq x_{ijv} \qquad \forall v, i > 0, j > 0 \qquad \mathbf{(12)}$$

In the expressions, *y* is the number of vehicles; C_v is the maximum loading of vehicle *v*; λ_v is the unit load cost of vehicle *v*, that is the maximum loading cost of vehicle *v*, maximum load of vehicle *v*; K is the distance from client *i* to client *j*; u_v is unit driving distance cost of vehicle *v*; d_i is the demand of client *i*; C_m is the smallest load of different kinds of vehicles.

In the model, expression (1) is the objective function to minimize all used vehicles and the total cost of vehicle distance, hereinto, the first item is the cost of used vehicles; the second item is the additional punishment item cost on the residual load while the vehicle is not full, which makes the vehicle to maximize loading ability; the third item is the cost of used vehicle traveling distance, while in the traditional OVRP, the objective function only has item 1 and item 3; Expression (2) and expression (3) limit vehicles must start from the depots, and finally don't need to return to depots; Expression (4) and expression (6) limit at least one truck can reach

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to each client, and provide them with the service and then leave; expression (7) limits each client's demand must be satisfied; expression (8) limits vehicle's load should not exceed the maximum load of vehicles; expression (9) limits the total load provided by vehicles; expression (10) limits the split delivery must be integer split; expression (11) and expression (12) limit all the vehicles.

THE DESIGN OF TABU SEARCH ALGORITHM

Tabu search algorithm[7-9] is a kind of global iterative optimization algorithm with strong local search ability, by introducing a flexible storage structure and the corresponding tabu criterion to avoid detour search, and through the despising criterion to forgive some taboo good states, ensuring that the diversified effective exploration can finally realize global optimization.

Initial solution

Tabu search algorithm starts to search process from an initial solution, according to the characteristics of SDOVRPHV, this paper adopts an improved heuristic algorithm to generate the initial solution[10]. For convenient expression, the following variables are defined: N is the clients set; T is the clients set without completing service; V is the set of provided vehicles; C_v is the load of vehicles V; RC_v is the carrying capacity that vehicles V can also load currently, e_i is the satisfied delivery quantity of client i, and $e_i \leq d$; q_v is the current load of vehicle v. The specific process of algorithm is described as follows:

Step 1 : Initialization $T = N - \{0\}$, $q_v = 0$, $RC_v = 0$, $e_i = 0 (i = 1, 2, ..., N)$.

Step 2 : If T is not null and V is empty, there is no initial solution, quit; Otherwise in T randomly select client i, and choose vehicle v with the largest load in V to provide client service, $q_v = \min\{C_v, d_i - e_i\}$, $RC_v = C_v - q_v$, $e_i = e_i + q_v$.

Step 3 : If $d_i - e_i = 0$, then in T the client i is deleted.

Step 4 : If $q_v = C_v$, then turn to step 8; otherwise to step 5.

Step 5 : In T randomly select next client j, vehicle v travels from the client i to client j to supply the service, $q_v = q_v + \min\{RC_v, d_j - e_j\}$, $RC_v = C_v - q_v$, $e_j = e_j + \min\{RC_v, d_j - e_j\}$.

Step 6 : If $d_j - e_j = 0$, then in T the client j is deleted.

Step 7 : If $C_v = q_v$, then turn to step 8; otherwise $i = j$, turn to step 5.

Step 8 : In set V delete v, update the set T, i.e., $V = V - \{v\}$.

Step 9 : Repeats the step 2 to step 9 until set t is empty.

Neighborhood structure

Neighborhood structure is one important concept in the optimization of tabu search algorithm[11], and its function is how to guide to produce a group of solution by a solution. In VRP and OVRP, generally 1-opt and 2-opt methods are used to produce new solutions. 1-opt usually chooses a client point in one path, and inserts it into another path; 2-opt usually in 2 paths respectively chooses a client point, to do exchange between two client point positions. Due to the client demand can be split in SDOVRPHV, 1-opt and 2-opt cannot be directly used in this problem, therefore, based on 1-opt and 2-opt this paper does some improvement to adapt to the need of questions.

(a) Improved 1-opt

Improved 1-opt is based on 1-opt, randomly selects a client point and inserts into another path, the position of the minimum distance increase caused by inserting the client is taken as the insertion point, at the same time, according to the current requirements of client and the different situations of the rest loading capacity of vehicles, while in the insertion, there are two methods for selection, direct insertion or at the same time to split or merge the client's demand to realize the reasonable split of client demand, and reduce the total cost of vehicle and traveling distance. The formalization description is as follows:

Step 1 : Initialization, in current solution randomly select client i and two vehicles v_1 and v_2, which are corresponding to two paths, v_1 is requested to carry the load $0 < RC_{v_1} < C_{v_2}$, client i is in the route of vehicle v_2, the carrying load of v_2 at client point i is $q_i^{v_2}$, and $\theta = \min\{q_t^{v_2}, RC_{v_1}\}$.

Step 2 : If v_1 doesn't pass client point i and $\theta = q_i^{v_2}$, then i is inserted into the position that produces minimum distance increase in the route of vehicle v_1, i is deleted from the route of v_2, $q_i^{v_1} = \theta$, $q_i^{v_2} = 0$.

Step 3 : If v_1 doesn't pass client point i and $\theta = RC_v$, then i is inserted into the position that produces minimum distance increase in the route of vehicle v_1, i is deleted from the route of v_2, $q_i^{v_1} = \theta$, $q_i^{v_2} = q_i^{v_2} - \theta$.

Step 4 : If v_1 passes client point i and $\theta = q_i^{v_2}$, then i is deleted from the route of v_2, $q_i^{v_1} = q_i^{v_1} + \theta$, $q_i^{v_2} = 0$.

(b) Improved 2-opt

Improved 2-opt is based on 2-opt that randomly chooses two paths in current solution, in these two paths respectively and randomly selects a client, and exchanges these two clients. In the exchange process, according to the loading capacity of vehicles and split conditions of client demand, the splits which are not in favor of optimization solution are merged, direct exchanges the clients who do not involve in the split demand, in order to reduce the total cost of vehicles and traveling distance. The formalization description is as follows:

Step 1 : Initialization, in current solutions randomly select client$i$ and two vehicles v_1 and v_2, which are corresponding to two paths, in the paths of v_1 and v_2 one client i or j is randomly selected, the carrying load of vehicle v is $q_i^{v_1}$ at client point i, the carrying load of vehicle v is $q_j^{v_2}$ at client point j.

Step 2 : If v_1 doesn't pass client point j and v_2 passes client point i, then delete the i from the route of vehicle v_1, the carrying load of vehicle v_2 to client i is $q_i^{v_2} = q_i^{v_2} + q_i^{v_1}$, insert j into the position of client i in the route of path v_1, $q_j^{v_1} = q_j^{v_2}$.

Step 3 : If v_1 passes client point j, and v_2 doesn't pass client i, then delete the j from the route of vehicle v_2, the carrying load of vehicle v_1 to client j is $q_j^{v_1} = q_j^{v_1} + q_j^{v_2}$, insert i into the position of client j in the route of path v_2, $q_i^{v_2} = q_i^{v_1}$.

Step 4 : If v_1 passes client point j, and v_2 passes client point i, then delete the i from the route of vehicle v_1, the carrying load of vehicle v_2 to client i is $q_i^{v_2} = q_i^{v_2} + q_i^{v_1}$, delete the j from the route of vehicle v_2, the carrying load of vehicle v_1 to client j is $q_j^{v_1} = q_j^{v_1} + q_j^{v_2}$.

Step 5 : If v_1 doesn't pass client point j, and v_2 doesn't pass client point i, insert i into the position of client j in the route of path v_2, $q_i^{v_2} = q_i^{v_1}$, insert j into the position of client i in the route of path v_1, $q_j^{v_1} = q_j^{v_2}$.

Taboo object, taboo length, the candidate solution, despising criterion and termination criterion

In the algorithm, this paper puts each iterative optimal solution as taboo object into the tabu list; the selection of tabu length depends on the problem scale, it was taken as the square root of the problem scale; the candidate solution is selected in the field of current solution, selects respectively the five optimal as candidate solution from the field of every state; despising criterion adopts the criteria based on the adaptive value; the termination criterion adopts when iterations reach to a specified value, or in a given continuous iteration steps the current best solution has no change to terminate the algorithm.

SIMULATION

To describe the complexity and uncertainty in the reality, in the experiment the coordinates of client points use the method of random generation, client's demands also adopt the same way, and three types of vehicles are supposed to provide delivery service.

Molded validation

To validate the validity of model, this paper presents an example specification with number of 10 clients, the client's detailed information is shown in TABLE 1, among the table, the client 0 is depot; three kinds of

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vehicle load are 50, 40, and 30, and in the traditional OVRP all vehicle's load is 50; all the vehicle's unit load cost $\lambda_v = 15$, driving distance cost $u_v = 10$.

TABLE 1 : The basic information of 10 clients

clients	X	Y	demand
0	50	50	0
1	17	28	45
2	36	14	49
3	33	81	36
4	36	22	47
5	40	72	46
6	87	20	10
7	14	77	33
8	42	12	22
9	18	71	9
10	7	50	20

In the experiment, in the literature[2] adopting tabu search algorithm for the traditional OVRP the total cost is 10547, in this paper the total cost solving SDOVRPHV is 9882, which indicates that SDOVRPHV can reduce vehicle traveling distance and total cost, also verifies the effectiveness of the model. The optimal path results are both shown in TABLE 2, hereinto, T-OVRP represents the traditional OVRP path table; SDOVPRHV represents OVRP path table with split demand and different kinds of vehicles; TV represents the vehicles corresponding to SDOVPRHV.

TABLE 2 : The optimal route results of 10 clients

T-OVRP	SDOVPRHV	TV
0-2(49)	0-7(33)-10(17)	50
0-9(9)-7(33)	0-8(22)-2(25)	50
0-1(45)	0-9(9)-3(41)	50
0-3(44)	0-4(40)	40
0-10(20)	0-4(7)-2(24)-1(5)-10(3)	40
0-5(46)	0-1(40)	40
0-4(47)	0-5(30)	30
0-8(22)-6(10)	0-6(10)-5(16)-3(3)	30

Parameter settings

In this paper, five experiment examples are respectively done with clients number 10, 20, 30, 40, and 50 to $A = \{\lambda_v = 15, u_v = 10\}$, $B = \{\lambda_v = 15, u_v = 15\}$, $C = \{\lambda_v = 10, u_v = 15\}$ comparing with the traditional OVRP results in literature[2] adopting tabu search algorithm, which are shown in TABLE 3. When $\lambda_v = 15$, $u_v = 10$ and the client number are 10, 20, 30, 40,50, the algorithm result is the best, therefore, in the following experiments, all the vehicle's unit load cost are set as $\lambda_v = 15$, the unit running cost $u_v = 10$.

TABLE 3 : The saving cost of SDOVRPHV under different parameters

Clients number	$\lambda_v = 15$, $u_v = 10$	$\lambda_v = 15$, $u_v = 15$	$\lambda_v = 10$, $u_v = 15$
10	1015	359	-910
20	1233	533	-1552
30	1612	712	-2285
40	1237	-519	-3084
50	97	-1069	-4354

Analysis and compare with the traditional OVRP

Based on the experiment examples with client numbers 10,20,30,40, and 50, comparing with the tabu search algorithm in literature[2] of traditional OVRP results, the results are shown in TABLE 4, each column shows as follows: N is client's number; D is the total client's demand; T is the type of vehicles; SD is the final assembly capacity to clients provided by vehicles; T-OVRP is a total cost of traditional OVRP; SDOVPRHV is the OVRP total cost of different kind of vehicles with split demand; GAP is the saving rate of the total cost.

TABLE 4 : Compare of experiment results between SDVORPHV and traditional OVRP

No	N	D	T	SD	SDOVPRHV	T-OVRP	GAP/ (%)
1	10	159	50 40 30	170	5750	6867	16
2	10	203	50 40 30	210	8176	9308	12
3	10	268	50 40 30	270	9519	10634	10
4	20	432	100 80 60	440	14122	15454	9
5	20	463	100 80 60	480	13800	15324	10
6	20	501	100 80 60	520	14975	16897	11
7	30	560	150 120 90	600	17376	19314	10
8	30	688	150 120 90	720	21001	22843	8
9	30	893	150 120 90	930	22519	24693	9
10	40	712	150 120 90	780	22050	23518	6
11	40	863	150 120 90	930	24666	25954	5
12	40	1147	150 120 90	1230	31840	31091	-2
13	50	967	150 120 90	1050	29660	30034	1
14	50	1174	150 120 90	1260	32606	32651	0.2
15	50	1488	150 120 90	1560	41769	40591	-3

TABLE 4 shows in the above examples, comparing SDOVRPHV and traditional OVRP, the total cost reducing range is about -3% to 16%, in average it reduces by 6.8%, it is shown SDOVRPHV can save the total cost. In the experimental results, to the client number being 10, 20, 30, the saving rate of total cost is in 8%-16%, to the examples with client number being 40 and 50, the total cost saving rates is between -3% to 6%, but the SDOVRPHV total cost is greater than the traditional OVRP total cost, and comparing with the examples of client number being 10, 20, and 30, the saving rate of total cost of SDOVRPHV is relative decreased.

In TABLE 4 there appears negative saving rate in the examples 12 and 15, the following a large scale of experiments are done to the examples with clients' number 40 and 50.

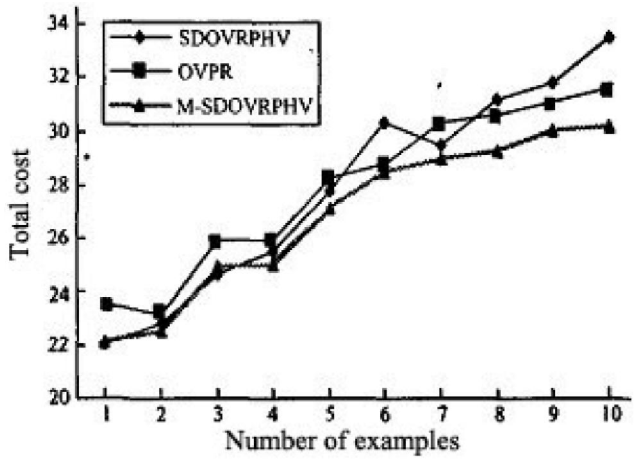

Figure 1 : The compare results of examples with clients' number 40

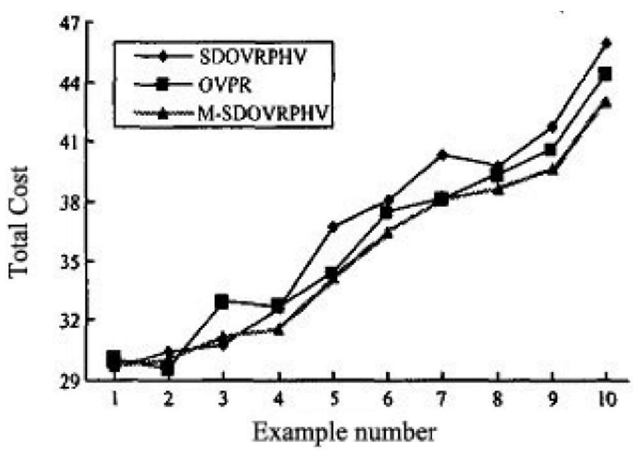

Figure 2 : The compare results of examples with client's number 50

This paper chooses 10 examples to do experiments, from figure 1 and 2; the total cost of SDOVRPHV is greater than the traditional OVPR total cost to some examples. In figure 1, to the 10 examples with client number being 40, there are four SDOVRPHV total costs greater than the total cost of traditional OVRP. In figure 2, to the 10 examples with client numbers being 50, there are eight SDOVRPHV total costs greater than the traditional OVRP.

In the examples with clients number being 40 and 50, this paper adjusts the model parameter C_m as C_m/ 2 in expression (9), strengthens the constraints of provided vehicle assembled capacity, reduces vehicle cost, makes the split rationalization, and compares with the traditional OVRP, the results are shown as SDOVRPHV and OVRP in figure 1 and 2, hereinto the SDOVRPHV total cost of 10 examples with client number 40 is less than traditional OVRP total cost; the 9 SDOVRPHV total cost from 10 examples with client number 50 is less than traditional OVRP total cost; in general, good results are obtained.

CONCLUSION

This paper studies the open vehicle routing problem of different kinds of vehicles with split demand, the problem is described, based on the integer programming to establish its mathematical model, and designs the tabu search algorithm for the problem, comparing the results with the traditional OVRP problems, the good results are obtained. Thus in certain circumstances through the split delivery, maximizing the use of vehicle load can reduce the total cost of vehicles and traveling distance, these provide certain reference for future research work and in practice to solve the vehicle routing problem.

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