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Spatiotemporal distance embedded hybrid ant colony algorithm for a kind of vehicle routing problem with constraints

Key words: Vehicle routing problem with constraints (VRPC); Spatiotemporal distance function; Labor division strategy; Ant colony algorithm (ACO)

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Motivation

- Most of **vehicle routing problem (VRP) variants** are built on logistics networks. However, the demand for route planning is no longer limited to logistics and distribution, but reflected in aspects such as car-sharing traveling.
- Compared with VRP variants, the vehicle routing problem in the car-sharing environment has more stringent **spatiotemporal constraints**.
- **Ant colony algorithm (ACO)** is an effective method for solving VRPs, but it is easily trapped in local extremes and difficult to jump out.

Model

Based on the problem characteristics, we define a kind of **vehicle routing problem with constraints (VRPC)** model.

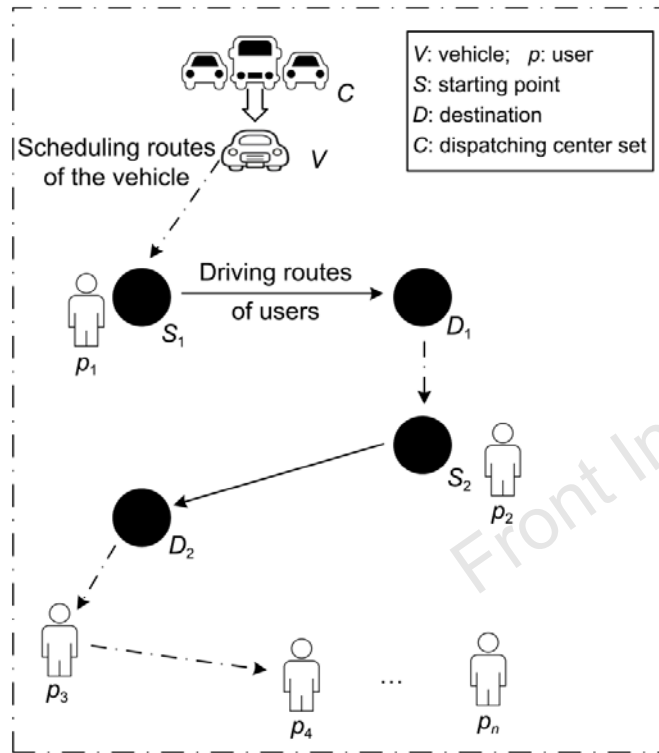


Fig. 1 Vehicle service process in the vehicle routing problem with constraints

$$\text{Cost}_{\min} = C_v + C_s + C_f + C_t,$$

$$C_v = Z_1 K,$$

$$C_s = Z_2 \left[\sum_{i \in P} \sum_{j \in P} \sum_{k \in [1, K]} \left(\text{dist}(D_i, S_j) X_{ijk} \right) + \sum_{i \in P} \sum_{k \in [1, K]} \left(\text{dist}(C, S_i) X_{cik} \right) + \sum_{i \in P} \sum_{k \in [1, K]} \left(\text{dist}(D_i, C) X_{ick} \right) \right],$$

$$C_f = Z_3 \sum_{i \in P} \text{dist}(S_i, D_i),$$

$$C_t = \sum_{i \in P} F_i, \quad \forall i \in P.$$

Method

First, the **spatiotemporal distance function** is established based on the spatiotemporal distribution characteristics of users.

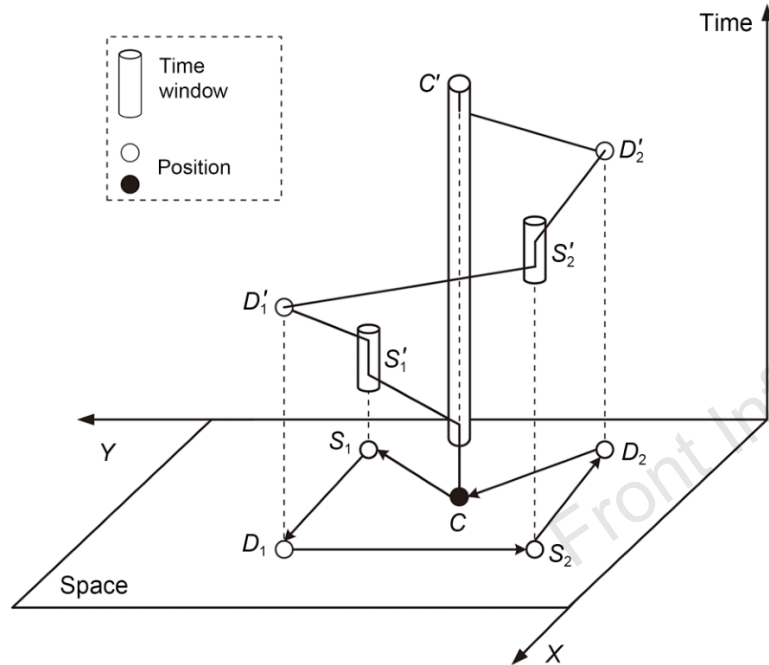


Fig. 2 Vehicle trajectory and user services of the vehicle routing problem with constraints

$$\text{dist}T_{ij} = \begin{cases} K_{t1}(e_j - T_{sj}), & T_{sj} < e_j, \\ 0, & e_j \leq T_{sj} \leq l_j, \\ K_{t2}(T_{sj} - l_j), & T_{sj} > l_j, \end{cases}$$

$$\forall i, j \in P \text{ and } e_i < e_j,$$

$$\text{dist}S_{ij} = \begin{cases} \text{dist}(D_i, S_j), & e_i \leq e_j, \\ \text{dist}(D_j, S_i), & e_i > e_j, \end{cases}$$

$$\forall i, j \in P,$$

$$\text{dist}ST_{ij} = K_T T \text{dist}T_{ij} + K_S T \text{dist}S_{ij}, \quad \forall i, j \in P.$$

Method

Second, a clustering method based on the spatiotemporal distance is designed, called the **spatiotemporal clustering algorithm (STCA)**. Subsequently, the initial solutions are constructed according to the clustering results.

Algorithm 1 Spatiotemporal clustering algorithm (STCA)

Input: datasets P, S , and D , time window $[e, l]$, cluster number z , and maximum clustering number $\text{Clu}_{\max}$

Output: set of clusters $C_1 = \{C_{11}, C_{12}, \dots, C_{1z}\}$

```
1  Data = { $P_1, S_1, D_1, [e_1, l_1]$ ;  $P_2, S_2, D_2, [e_2, l_2]$ ;  $\dots$ ;  $P_n, S_n, D_n, [e_n, l_n]$ }
2  Randomly select data of  $z$  users from Data as cluster center  $C_t$ 
3  repeat
4     $C_{1i} = \phi$  ( $1 \leq i \leq z$ ) // Cluster  $C_{1i}$ 
5    for  $j=1, 2, \dots, n$  do
6      Calculate the spatiotemporal distance  $\text{distST}_{ji}$  between user  $P_j$  and each clustering center  $C_{ti}$ 
7      Determine the cluster label of  $P_j$  based on the closest
```

... ..

Algorithm 2 Heuristic semi-random strategy

Input: clustering results $C_1 = \{C_{11}, C_{12}, \dots, C_{1z}\}$, and the number of initial solutions N

Output: initial solution set $S_1 = \{S_{11}, S_{12}, \dots, S_{1N}\}$

```
1  Set count=0
2  while count <  $N$  do
3    for  $i=1, 2, \dots, z$  do
4      Cluster  $C_{1i}$  randomly selected to become a sequentially ranked object or a randomly ranked object
5      if  $C_{1i} \in$  Sequentially ranked object
6        Sort the users of  $C_{1i}$  according to the time window order and obtain  $\text{Part}_i = \text{sort}\{C_{1i}\}$ 
7      else
```

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Method

Finally, we propose an **improved ant colony algorithm (IMFACO)** for routing optimization of VRPC, which can be divided into four parts.

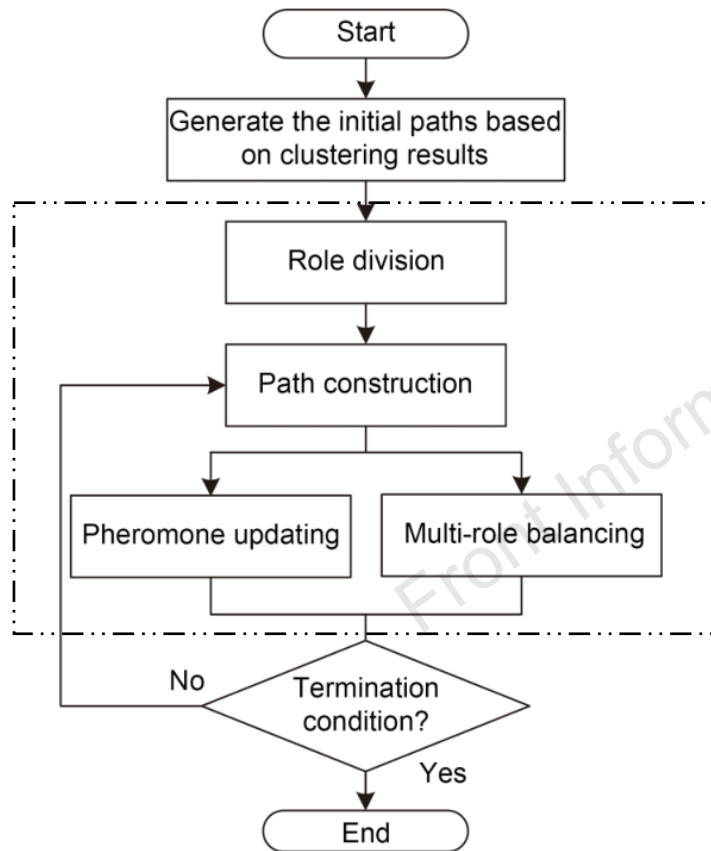


Fig. 5 Framework of the improved ant colony algorithm based on the mixed feedback mechanism

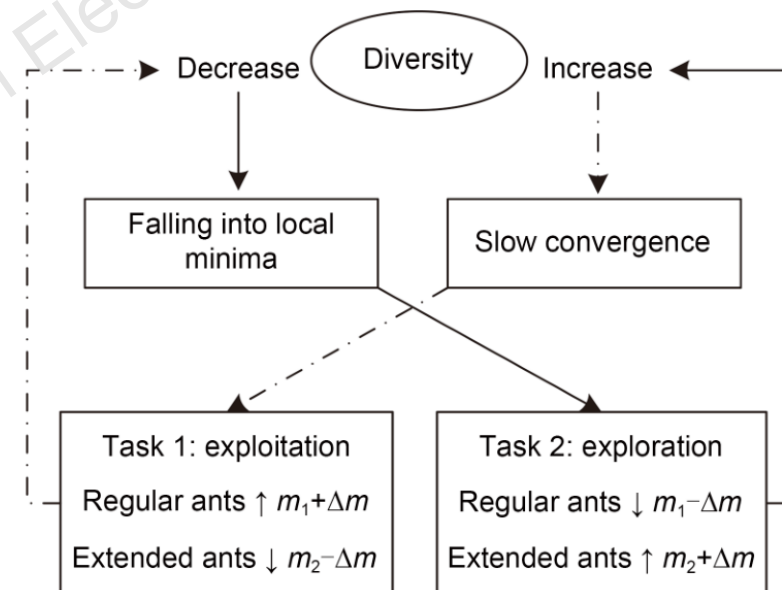


Fig. 8 Multi-role balancing mechanism

Major results

To assess the quality of the proposed algorithm, we first use the **test instances** for testing. Concerning the combined cost, our proposed algorithm has competitive cost compared to existing algorithms.

Table 4 Comparison results of VRPC test instances

Instance	Algorithm	Minimum	Average	Dev (%)	Instance	Algorithm	Minimum	Average	Dev (%)
C1 <i>n</i> =30	ACO	1074.7	1176.6	9.48	C5 <i>n</i> =60	ACO	2232.4	2516.6	12.73
	AADC	922.4	1050.9	13.94		AADC	2182.5	2441.4	11.86
	IWPA	891.5	983.9	10.36		IWPA	2201.8	2509.4	13.97
	IGA	947.4	1068.3	12.76		IGA	2182.5	2431.6	11.41
	HACA-ST	879.4	897.2	2.02		HACA-ST	2087.2	2170.5	3.99
C2 <i>n</i> =30	ACO	1097.3	1279.1	16.57	C6 <i>n</i> =60	ACO	1999.6	2306.8	15.36
	AADC	921.0	1026.3	11.44		AADC	1950.2	2217.2	13.69
	IWPA	1004.3	1127.7	12.29		IWPA	1903.4	2138.8	12.37
	IGA	988.6	1135.8	14.89		IGA	2067.2	2402.6	16.22
	HACA-ST	900.9	920.1	2.13		HACA-ST	1854.8	1929.5	4.03
C3 <i>n</i> =30	ACO	868.1	970.5	11.80	C7 <i>n</i> =100	ACO	3564.0	4205.9	18.01
	AADC	740.8	820.2	10.72		AADC	3434.4	3909.0	13.82
	IWPA	718.7	785.3	9.26		IWPA	3500.4	4072.8	16.35
	IGA	791.2	868.9	9.82		IGA	3564.0	4126.8	15.79
	HACA-ST	697.1	723.1	3.73		HACA-ST	3341.3	3553.8	6.34

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Major results

In addition, to further assess the solution performance of the algorithm in a realistic environment, two **scenarios instances** are designed based on the real city.

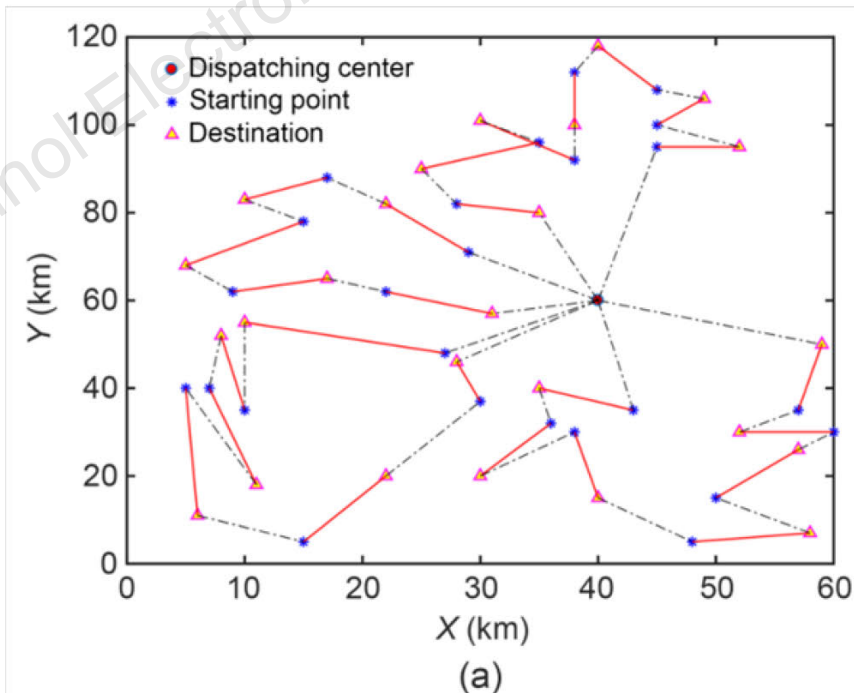
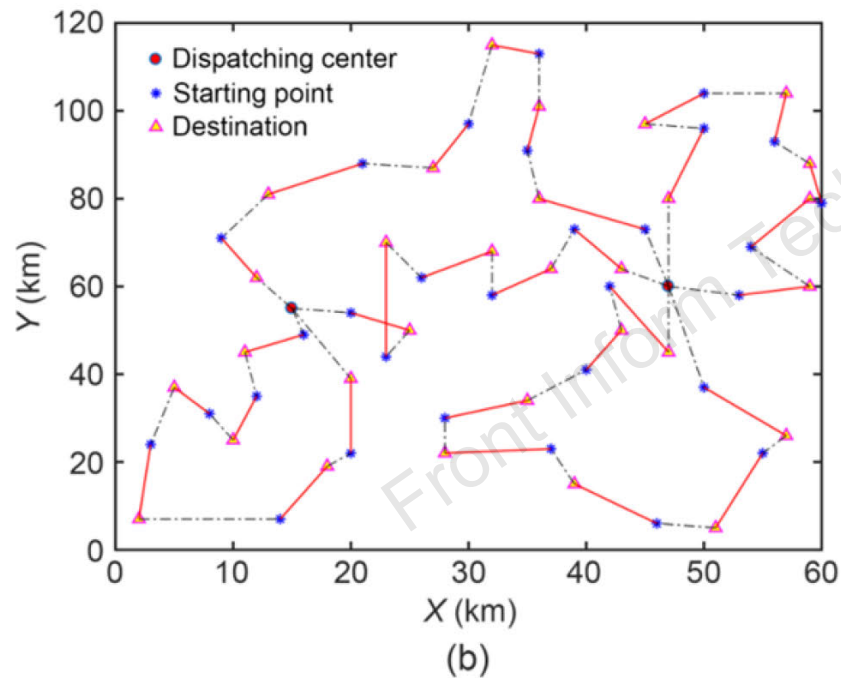


Fig. 11 Optimal routes of the scenario instances: (a) route of case 1; (b) route of case 2

Conclusions

- We investigate a kind of **VRPC** in the car-sharing mobility environment.
- We define a **spatiotemporal distance function** based on the temporal and spatial properties of users.
- We propose a **spatiotemporal distance embedded hybrid ant colony algorithm (HACA-ST)** to solve VRPC.



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