

Zhenhui FENG, Renbin XIAO, Mingzhi XIAO, 2025. Spatial crowdsourcing task allocation for heterogeneous multi-task hybrid scenarios: a model-embedded role division approach. *Frontiers of Information Technology & Electronic Engineering*, 26(7):1144-1163. <https://doi.org/10.1631/FITEE.2500035>

Spatial crowdsourcing task allocation for heterogeneous multi-task hybrid scenarios: a model-embedded role division approach

Key words: Spatial crowdsourcing (SC); Heterogeneous task; Role division; Attraction–repulsion mechanism; Individual sorting

Corresponding author: Renbin XIAO

E-mail: rbxiao@hust.edu.cn

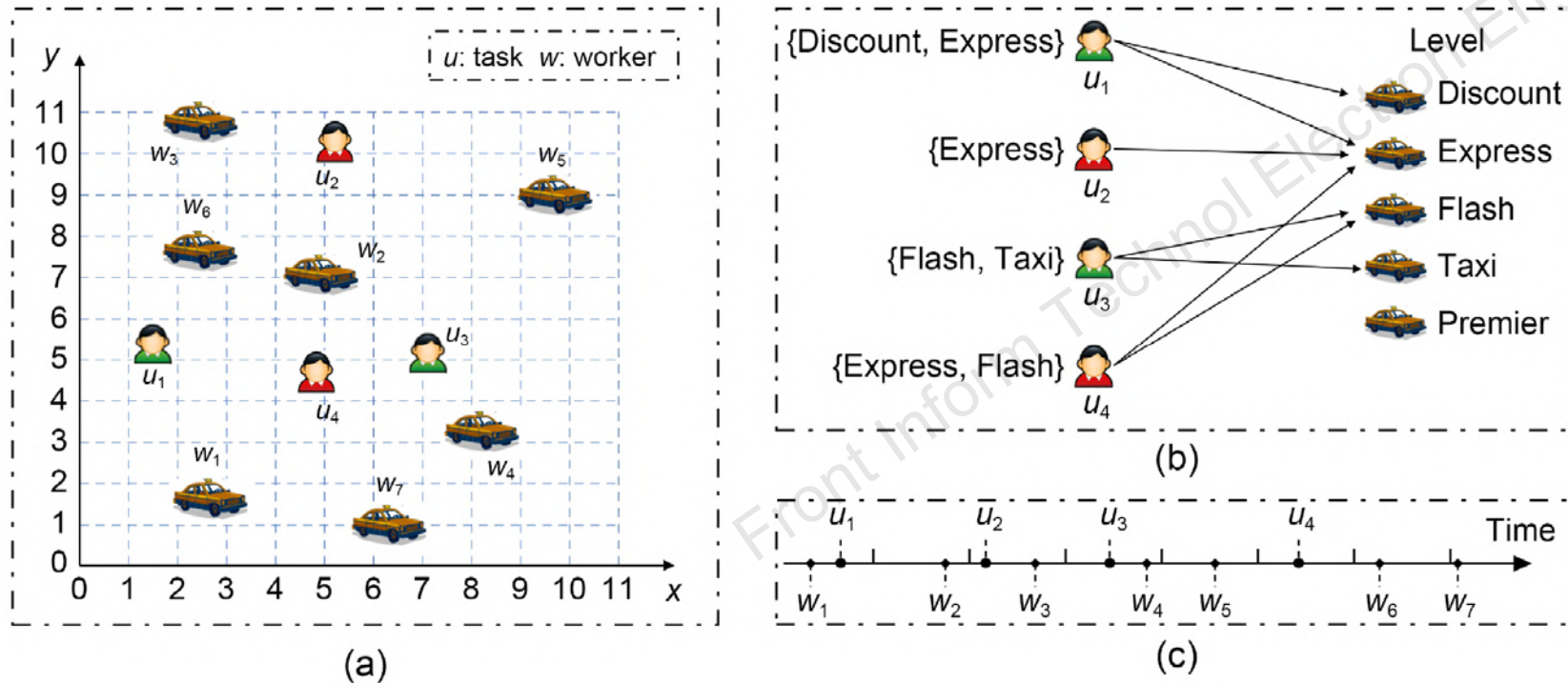
 ORCID: <https://orcid.org/0000-0003-0951-2734>

Motivation

- **Task allocation** is a critical problem in **spatial crowdsourcing**. We study its new challenges under the trend of increasingly flexible services and diverse user needs.
- Address the impracticality of static-scenario assumptions by studying online allocation for **dynamic environments** with unpredictable tasks/workers.
- Move beyond homogeneous models to deal with **heterogeneous multi-task allocation** (HMTA) in hybrid environments where tasks and workers have diverse attributes.

Problem

In response to the described scenario of spatial crowdsourcing, we define a kind of HMTA problem.



$$u_i = \langle \mathbf{l}u_i, Rl_i, h_i, s_i, e_i \rangle$$

$$w_j = \langle \mathbf{l}w_j, r_j, p_j, c_j, b_j, d_j \rangle$$

$$Rf(u_i, w_j) = [p_j \cdot h_i - C_d \cdot \text{dist}(\mathbf{l}w_j, \mathbf{l}u_i)] \cdot X_{ij}$$

$$UT = \sum_{u_i \in U', w_j \in W'} Rf(u_i, w_j) - \eta \sum_{u_i \in Uf} h_i$$

Fig. 1 Task allocation of a car-hailing scenario: (a) spatial distributions; (b) task requirements; (c) temporal distributions

Method

We propose the **role division approach embedded with individual sorting model** (RD-ISM) to address the problem. The method begins with data processing of perceived information, where we collect tuples of objects to be matched using **batch-based mode** (BBM).

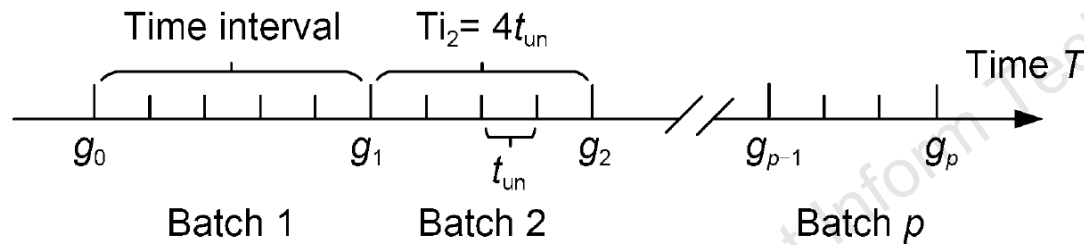


Fig. 2 Timeline diagram of the BBM

Algorithm 1 Batch-based mode

Input: Total time T and time interval T_i

Output: Task-worker matching results M within T

- 1 Set $M \leftarrow \emptyset$
- 2 After every time interval T_i , a batch p is obtained
- 3 **for** each batch $p \in T$ **do**
- 4 Collect a set of tasks U_p
- 5 Collect a set of workers W_p
- 6 Prioritize all objects according to the individual sorting model to obtain a task sequence
- 7 Based on the task sequence, perform matching based on the role division model and obtain a feasible matching $M_p \subseteq U_p \times W_p$
- 8 Let the matching result M_p be a feasible matching of batch p and output it

... ..

Method

During the allocation process, the **individual sorting model** is first introduced to determine the sequence of tasks and workers. Then, a **role division model** based on **attraction–repulsion mechanism** is designed to match tasks and workers.

Table 1 Mapping relationship between attraction–repulsion mechanism and task allocation

Attraction–repulsion mechanism	Task allocation
Agent	Worker
Role	Task
Environment	Task attributes
Role diversion	Task–worker matching
Overall role distribution	Matching results $M \subseteq U \times W$

Algorithm 2 RD-ISM

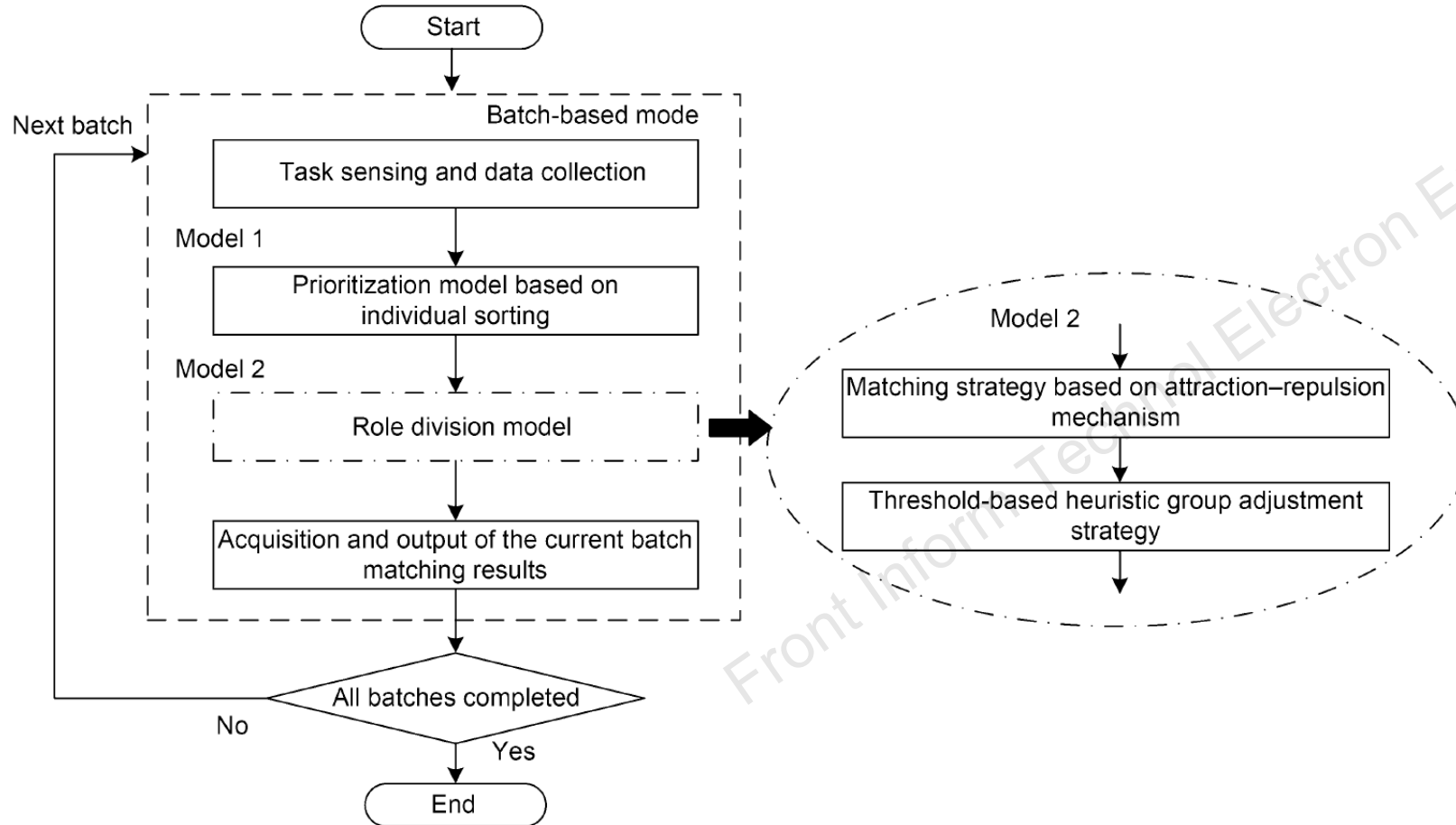
Input: Total time T and initial time interval T_i

Output: Matching results M

- 1 Set $M \leftarrow \emptyset$
- 2 Let $v \leftarrow \text{floor}(\ln(Rf_{\text{Max}}))$
- 3 Set $\omega_z = 1$, where $z = 0, 1, \dots, v$
- 4 Calculate the probability $\mathbf{P} = (P_0, P_1, \dots, P_v)$ according to Eq. (25)
- 5 After every time interval T_i , a batch p is obtained
- 6 **for** each $p \in T$ **do**
- 7 Collect the task set U_p and the worker set W_p
- 8 Calculate the priority $\text{Pr}(\cdot)$ of objects and EU and EW according to the individual sorting model

... ..

Method



After individual sorting and role division, the **current batch matching results** are obtained. In the real-time task allocation process, the algorithm can achieve the **final matching results** of all objects following **multiple batches of iteration**.

Fig. 3 Overall framework of RD-ISM

Major results

To evaluate the performance of RD-ISM, we design two distinct sets of test cases: **synthetic dataset instances** and **real-world dataset instances**.

Table 2 Dataset statistics and parameter settings

Parameter	Settings and statistics	
	Real-world dataset	Synthetic dataset
$N=4 U = W $	2500, 5000 , 10 000, 20 000	5000, 10 000, 20 000 , 40 000, 80 000
Time range (min)	[0, 300]	[0, 500]
Spatial range	Latitude and longitude to coordinates	Randomly distributed within 30 km×30 km area
Task requirements and worker levels R	{1, 2, 3, 4}	{1, 2, 3, 4}
Unit service price pr (CNY)	{1, 2, 3, 4}	{1, 2, 3, 4}
Worker service radius c (km)	10	5, 10 , 15, 20
Unit distance cost C_d (CNY/km)	0.8	0.8
Dissatisfaction coefficient η	0.1	0.1
Expected value μ of task service cost h	20, 25 , 30, 35, 40	20, 25 , 30, 35, 40

Bold entries represent the default settings used during the experiment

Major results

In the above instances, the **effectiveness** of RD-ISM in solving the HMTA problem was verified through comparisons with other algorithms. Additionally, we investigated the impact of different parameter values on performance and validated the **scalability** of the method.

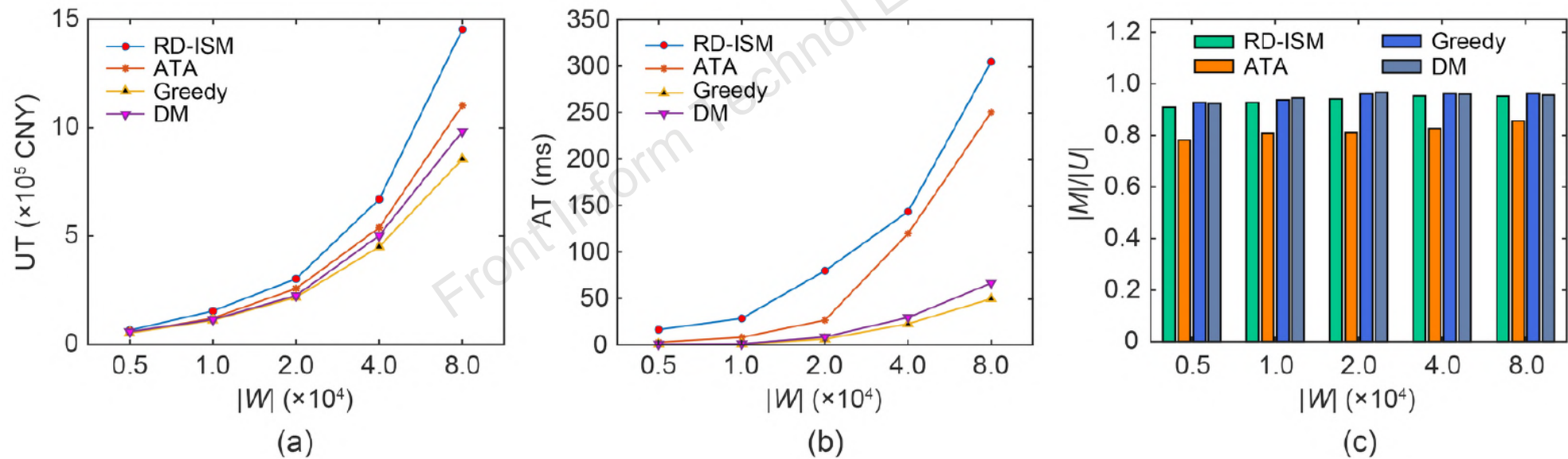


Fig. 4 Comparison of results from varying $|W|$: (a) UT; (b) AT; (c) $|M|/|U|$

Conclusions

- Define and formalize **HMTA** for hybrid heterogeneous scenarios, optimizing both direct allocation benefits and user satisfaction metrics.
- Design a **role-division approach** with individual sorting and attraction–repulsion mechanisms for spatiotemporal priority-based worker–task matching via iterative batch processing.
- Validate the method's **performance** and **scalability** through comparative experiments on real-world/synthetic datasets and parameter sensitivity analysis.



Zhenhui FENG received his MS degree in control science and engineering from China University of Petroleum in 2018 and his PhD degree in artificial intelligence from Huazhong University of Science and Technology in 2025. His research interests focus on collective intelligence and spatiotemporal computing.



Renbin XIAO is currently a professor and PhD supervisor at School of Artificial Intelligence and Automation, Huazhong University of Science and Technology. He received his PhD degree from Huazhong University of Science and Technology in 1993, majoring in systems engineering. He has published more than 10 academic monographs and over 300 academic papers. He has presided 11 projects of the National Natural Science Foundation of China. He has received one Natural Science Award of the Ministry of Education and four Natural Science Awards and Scientific & Technological Progress Awards of Hubei Province, China. Currently, his main research interests are collective intelligence, large-scale personalized customization, complex systems, and complexity science.



Mingzhi XIAO is currently a teaching assistant at Wuchang Shouyi University. He holds an MS degree and his research is focused on artificial intelligence and image recognition.