



Multi-Armed Bandits Based Task Selection of A Mobile Crowdsensing Worker

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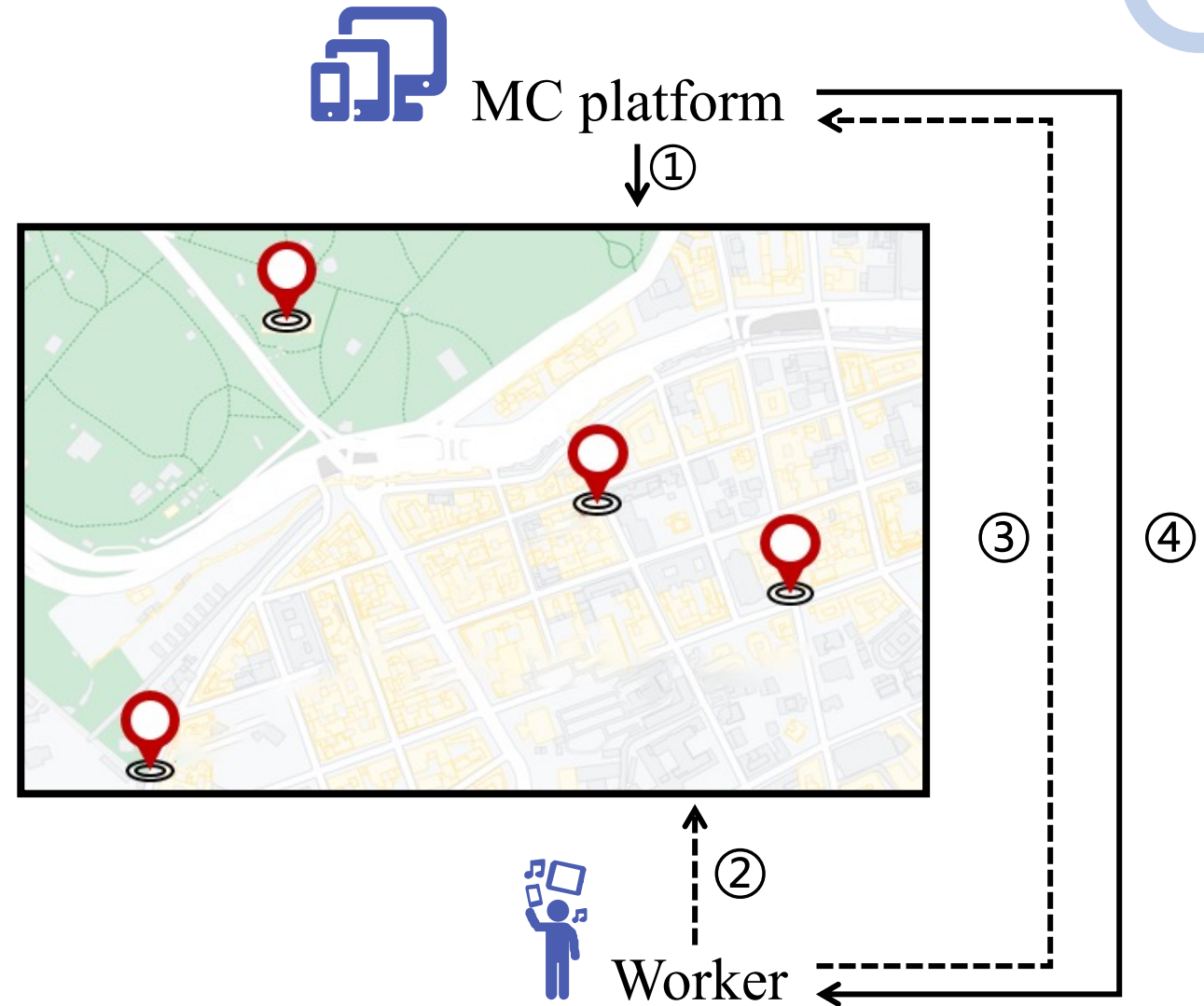
Smart devices

Embedded sensors

Wireless networks

Mobile Crowdsensing (MC)

- ① The MC platform publishes sensing tasks.
- ② Workers decide on task selection and move to execute tasks.
- ③ Workers collect and submit data to the MC platform.
- ④ The MC platform pays workers corresponding reward.



Background

Mobile Crowdsensing



MC platform

Target

- maximize the number of tasks
- maximize the coverage of tasks
-

Ideal assumption

- workers always obey task assignment
- ignore the entitlement of workers



Worker

★ Target : Profit maximization

Task selection

Background

- Scenario
 - Unknown reward information
 - Task execution \implies Resource consumption
 - Position transfer \implies Extra cost / Traveling cost
- Constraints
 - Smart devices
 - Worker preference
 - Platform requirement
- Target
 - Profit maximization
 - \longleftarrow (Total reward - Total traveling cost)



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System model

Finite rounds



Time is slotted. \Rightarrow



Before the system runs:

Tasks

- unknown
- heterogeneous
- location-based

Smart Devices

- limited resource (\mathcal{B})

In each round:

Task Selection



Specific standard



Position Transfer



Traveling cost



Task execution



Resource consumption

Problem Formulation

reward traveling cost

$$\text{Maximize : } \mathbb{E} \left[\sum_{t=1}^{t(\mathcal{B})} \left(\sum_{s_i \in \mathcal{S}} r_i^t \cdot \mathbb{I}_i^t - \sum_{s_i, s_j \in \mathcal{S}} c_{ij} \cdot \mathbb{I}_i^{t-1} \cdot \mathbb{I}_j^t \right) \right]$$

Subject to : $c_{ij} = 0$ for $l_i^{t-1} \rightarrow l_j^t$ where $i = j$

$$\sum_{t=1}^{t(\mathcal{B})} \sum_{s_i \in \mathcal{S}} \mathbb{I}_i^t \cdot b_i^t \leq \mathcal{B}$$
$$\left[\begin{array}{l} \sum_{s_i \in \mathcal{S}} \mathbb{I}_i^t = 1 \text{ for } \forall t \geq 1 \\ \mathbb{I}_i^t \in \{0, 1\} \text{ for } \forall t \geq 1, s_i \in \mathcal{S} \end{array} \right]$$

○ Profit Maximization.

○ Traveling cost.

○ Limited resources.

1. At the same time, any task only has two states of being executed and not executed.
2. In each round, only one task is conducted by the worker.



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Basic Solution

Unknown task information

- Unaware of the reward information of the tasks.
- Solution : Reinforcement Learning Technique.

Profit maximization

- Maximize total profit \approx maximize total reward while minimize total traveling cost.
- Solution : Epoch-style Algorithm.

- ✓ A Multi-Armed Bandit.
- exploration-exploitation dilemma;
- upper confidence bound strategy.

✓ UCB2 Strategy.

- epoch-style strategy;

$$\hat{r}_i(t) = \bar{r}_i(t) + \sqrt{\frac{(1 + \alpha) \ln(\frac{et}{\lceil \tau(E_i(t)) \rceil})}{2 \lceil \tau(E_i(t)) \rceil}}$$

average reward

adjustment item

Constraint 1 : Smart Device

1. Task execution leads to continuous **resource consumption** (e.g., battery energy).
2. Resource consumption is **negligible in position transfer**.

Problems caused by constraint 1

1. Trade-off between reward and resource consumption.
2. Loss of total profit.



Adjustment to Basic Solution

- **Learn** the reward information and **resource consumption** of the task.
- Selection Standard.

$$i_{now} = \operatorname{argmax}_{s_i \in \mathcal{S}} \left((\bar{r}_i(t) + \sqrt{\frac{(1+\alpha) \ln(\frac{et}{|\tau(E_i(t))|})}{2|\tau(E_i(t))|}}) / \bar{b}_i(t) \right)$$

UCB-based reward

Average resource consumption

Constraint 2 : Worker Preference

1. The connotation of personal preferences is more **complicated** in actual situations.
2. Workers prefer **closer locations** and **infrequent movements**.

Problems caused by constraint 2

1. Trade-off between the previous selection standard and the traveling-cost-related preference.
2. Loss of total profit.



Adjustment to Previous Solution

- Take the traveling-cost-related preference as a **penalty**.
- Selection Standard :

$$i_{now} = \operatorname{argmax}_{s_i \in \mathcal{S}} \left(\hat{r}_i(t) / \bar{b}_i(t) - \varrho_1 p_{i_{old}i}(t) \right)$$

Previous selection
standard

Traveling-cost-related
preference

Constraint 3 : Platform Requirement

1. It is **not advisable** to view the MC process from **only one perspective**.
2. The platform has expectation for the number of rounds of task execution (called **balance**).

Problems caused by constraint 3

1. More complex trade-off due to the balance-related requirement.
2. A negative impact on the entitlement of workers in the long run.



Adjustment to Previous Solution

- Introduce the **virtual queue**.

$$Q_i(t) = \max \{ 0, Q_i(t - 1) + e_i - \mathbb{I}\{i_{t-1} = i\} \}$$

- Selection Standard :

$$i_{now} = \operatorname{argmax}_{s_i \in \mathcal{S}} \left(\underbrace{\hat{r}_i(t) / \bar{b}_i(t)}_{\text{Previous selection standard}} - \varrho_1 \cdot p_{i_{old}i}(t) + \varrho_2 \cdot Q_i(t) \right)$$

Previous selection standard

The balance-related requirement.



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Performance Evaluation



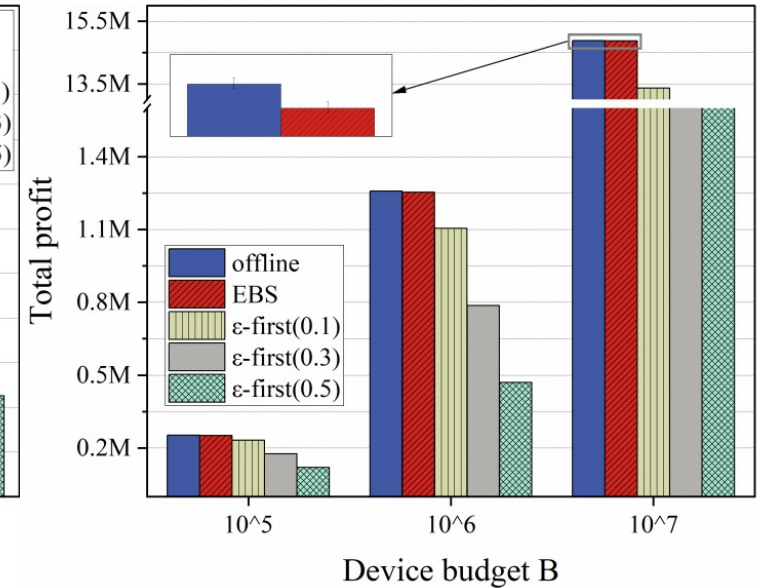
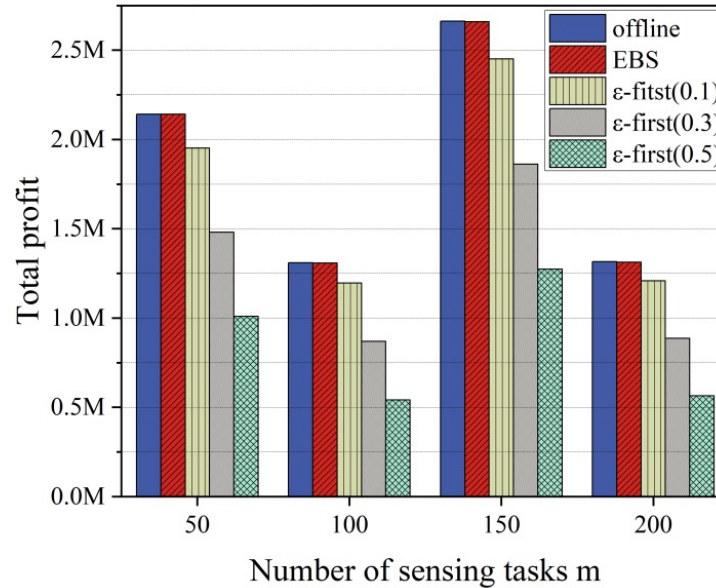
Metrics

- ◆ total profit
- ◆ total traveling cost
- ◆ execution rounds of tasks

Algorithms

- ◆ EBS (constraint 1)
- ◆ PAS (constraint 2)
- ◆ BAS (constraint 3)
- ◆ offline algorithm
- ◆ ϵ -first algorithm ($\epsilon \in \{0.1, 0.3, 0.5\}$)

Evaluation result of EBS

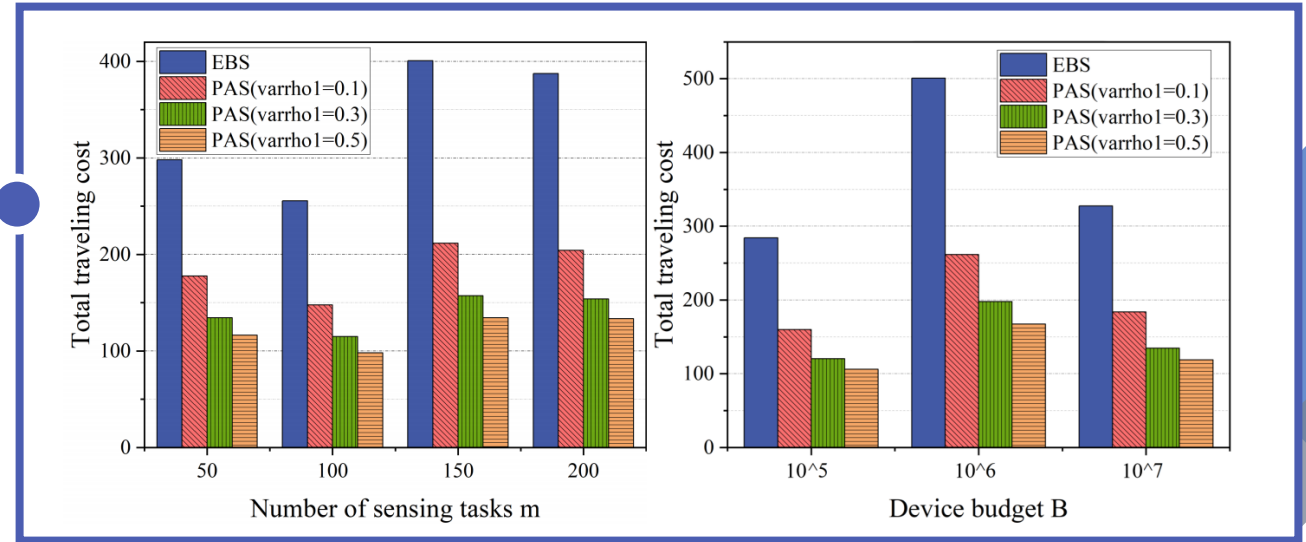


- The difference in the number of tasks and the device budget doesn't affect the performance of EBS.
- The total profit achieved by EBS has significantly better results than the ϵ -first algorithm.

Evaluation result of PAS

Total traveling cost

- PAS effectively reduces the total traveling cost.
- With the increase of ϱ_1 , the reduction is more significant.



Total profit

- With the reduction in total traveling cost, the total profit slightly increases.
- PAS has higher usability in scenarios where the traveling cost between tasks is high.

TABLE III
COMPARISON OF PAS AND EBS UNDER DIFFERENT TASK NUMBERS

task number m	metrics	PAS(0.1)	PAS(0.3)	PAS(0.5)
50	traveling cost	-40.40%	-54.91%	-60.98%
	total profit	+0.10%	+0.14%	+0.16%
100	traveling cost	-42.24%	-55.02%	-61.68%
	total profit	+0.05%	+0.07%	+0.08%
150	traveling cost	-47.22%	-60.80%	-66.44%
	total profit	+0.08%	+0.11%	+0.12%
200	traveling cost	-47.29%	-60.30%	-65.55%
	total profit	+0.08%	+0.10%	+0.13%

The table shows the comparison results of PAS with different values of ϱ_1 and EBS under different task numbers in specific metrics.

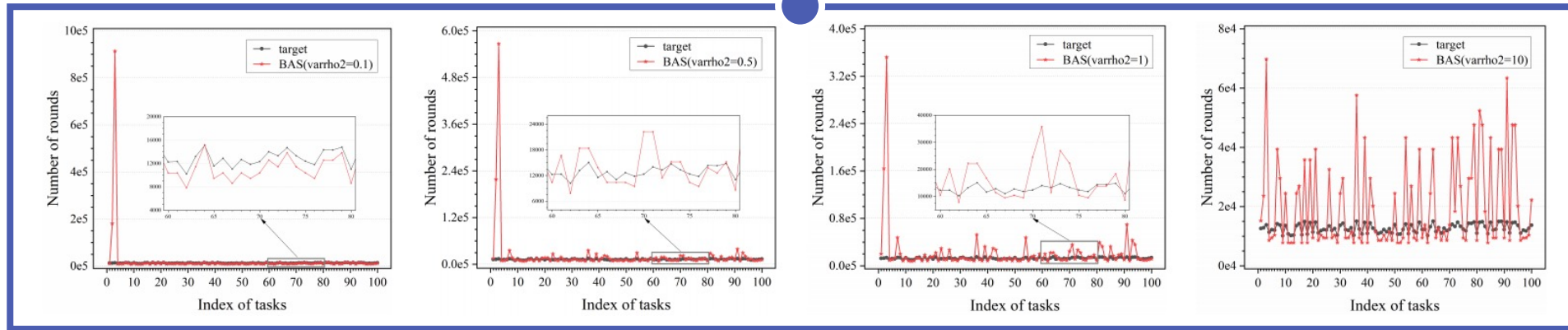
TABLE IV
COMPARISON OF PAS AND EBS UNDER DIFFERENT DEVICE BUDGETS

device budget B	metrics	PAS(0.1)	PAS(0.3)	PAS(0.5)
10^5	traveling cost	-43.74%	-57.67%	-62.73%
	total profit	+0.78%	+1.00%	+1.10%
10^6	traveling cost	-47.74%	-60.52%	-66.58%
	total profit	+0.21%	+0.25%	+0.30%
10^7	traveling cost	-43.87%	-58.89%	-63.71%
	total profit	+0.006%	+0.010%	+0.011%

The table shows the relative differences of PAS with different values of ϱ_1 compared with EBS in specific metrics under different device budgets.

Evaluation result of BAS

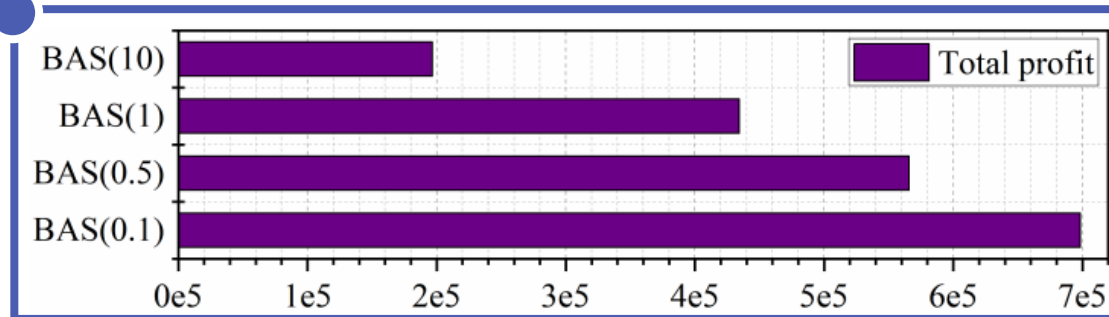
Execution rounds of tasks



- With the increase of ϱ_2 , the execution rounds of tasks become more balanced.
- The proportion of tasks whose execution rounds meets the requirement of the platform shows an upward trend.

Total profit

- The achieved total profit by BAS decreases significantly since the worker compromises more with the platform.





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— Summary

- ◆ View the Mobile Crowdsensing process from the perspective of an individual worker.
- ◆ Consider a scenario which is in line with our reality and further deal with possible constraints from different perspectives.
- ◆ Extensive simulations based on real-world verify the significant performance of our algorithms.

— Future work

- ◆ More realistic scenarios.
- ◆ Multiple workers.



Thank you!

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