Incentive Mechanisms for Pavement Crowdsensing with a Platform-driven Greedy Algorithm

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Abstract

Crowdsensing nowadays is regarded as an effective method to collect specific data due to its pervasiveness and convenience. There are projects using crowdsensing to collect pavement condition data. However, how to properly motivate users to participate in crowdsensing tasks with a low platform cost remains an open question. In our research, we model the pavement crowdsensing problem and design new incentive mechanisms based on a platform-driven greedy algorithm. The rewards of sensing tasks are determined by the specific incentive mechanisms. With this algorithm, the user selects the sensing task that can provide the highest net profit margin. These incentive mechanisms are evaluated and compared in different scenarios in terms of the platform cost and the overall task completion time through extensive simulations. Our methods can avoid the cost explosion problem observed in data-reverse-auction incentive mechanisms, and the best of them can reduce the overall completion time by half compared to task-reverse-auction incentive mechanisms.

Keywords: crowdsensing, pavement monitoring, monetary incentive, incentive mechanism

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1 Introduction

As road infrastructure continues to increase in size and complexity, new and innovative solutions must be developed to cope with road degradation. Current methods used to collect road condition information do not mitigate the stress in covering 4.18 million miles of road in the U.S [1]. One viable solution is to create a crowdsensing platform for smartphone users to collect road pavement data. For example, detecting and reporting poor road conditions by using embedded cameras, accelerometers, and 4G/5G networks. To support such a network, an active user base must be established and maintained. Users' participation is at the heart of creating diverse data pools and addressing quality road condition information. The component needed to satiate users' drive, and to generate the aforementioned benefits, is described as the incentive mechanism.

As we want to motivate more people to participate in performing the sensing tasks, an appropriate incentive mechanism allows the platform to properly stimulate the users to work for the platform and bound/reduce *platform cost* and *overall completion time* of the sensing tasks, which is also called *total operation time* in this report.

In our research, the platform wants to economically collect pavement condition data for a certain target area. In this report, we introduce a set of incentive mechanisms and study how pavement crowdsensing may cover a target area with the lowest platform cost and the smallest total operation time. The incentive mechanisms we design are based on a platform-driven greedy algorithm, which motivates users to select sensing tasks that can provide the highest net profit margin. Each incentive mechanism has a unique reward generation formula, which is designed within the context of road coverage. We have evaluated 9 incentive mechanisms through simulations in terms of their platform costs and total operation times. Our results provide guidance in selecting the best incentive mechanism in different settings of pavement crowdsensing.

Here are the key contributions of our research:

- The incentive mechanisms we design can effectively avoid the cost explosion problem as users choose their sensing tasks before starting to work on them so that a sensing task can only be done by no more than one user.
- Our incentive mechanism enables users to select sensing tasks that offer the highest net profit margin based on a greedy algorithm.
- The total operation time or the overall completion time of our approach is reduced comparing to that of the task-reverse-auction incentive mechanism. Our research helps the pavement crowdsensing platform to find a solution to crowd-sense the target area within a limited budget.

The rest of the report is organized as follows. We first survey the related work in Section II. Then we introduce the research problem and its model in Section III and present our incentive mechanism solutions in Section IV. Section V describes how we construct simulations for evaluating the incentive mechanisms. Section VI shows and discusses the evaluation results and Section VII concludes this report.

2 Related Work

2.1 Existing monetary incentive mechanisms

Zhang [14] and Jamies [11] both assort incentive mechanisms by the types of incentives. In Jamies [11], monetary and non-monetary incentives are compared. Non-monetary incentive mechanisms [2, 3] rely on the continued participation of users due to intrinsic motivations. Monetary incentive mechanisms [4–10, 15, 16] rely on the direct backing of fiat money or indirect backing of fiat money through alternative currencies. As a result, using non-monetary incentives cannot assure that enough users participate in sensing tasks. According to a survey paper [14], monetary incentives will be more likely to motivate users to complete the sensing tasks. Therefore, a monetary incentive mechanism is more fitting for crowdsensing and will be considered in our research. However, some monetary incentive mechanisms [5,10] have different shortages such as a cost explosion problem [14] while others may not fit in our research scenarios because they target at achieving optimal data quality [6, 10] and fairness [11]. Here are some brief descriptions of three monetary incentive mechanisms.

- For task-reverse-auction incentive mechanisms [15–17], they use a task-reverse-auction format to design their incentive mechanisms. The users would bid on the tasks posted by the platform. Then, the user who bids the lowest price can get the opportunity to perform the sensing task.
- For data-reverse-auction incentive mechanisms [4, 10], they use a data-reverse-auction format to design incentive mechanisms. In the auction process, users offer their sensing data of tasks and their prices to the platform. Then the platform would select the data that satisfies its requirement and pay for the price.
- In the platform-centric model [6], it treats the crowdsensing problem as a Stackelberg game. By changing the reward of the task, both users and the platform would reach a Nash equilibrium.

2.2 Comparison with three types of incentive mechanisms

Most of the existing incentive mechanisms are designed by auction theory and game theory. In this subsection, we compare our incentive mechanisms with three existing types of incentive mechanisms.

For the task-reverse-auction incentive mechanisms [15–17], their auction style cannot guarantee that the platform selects the nearby users to complete the sensing tasks because of untruthful bids [16]. In this situation, the user who is far away from a sensing task can win the auction. Further distances result in a longer travel time for users. Thus, the task-reverse-auction incentive mechanisms need more time to complete all the sensing tasks than our incentive mechanisms.

For data-reverse-auction incentive mechanisms [4, 10], while multiple users collect the data for one sensing task, only one user's data can be accepted by the platform. In other words, other users' data is wasted. As a result, this type of incentive mechanisms increase costs for car fuel, personal free time, and etc. For our incentive mechanisms, users can select the sensing task before they go to collect the data. Thus, the cost explosion problem can be avoided.

The platform-centric model [6] assumes that the platform has an unlimited budget. Therefore, it can find an optimal solution to get the highest-quality data available to the platform. Nevertheless, this incentive mechanism still has its limitations that the platform usually has a limited budget in practice use, which can be perfectly solved by our incentive mechanism.

3 Research Problem and Its Model

For our research problem, the platform needs data of pavement conditions in certain areas. Thus, we should motivate the users using the platform to collect the data. In this case, our research objective is to design an appropriate incentive mechanism to help the platform achieve an area coverage target with a low cost and total operation time. Based on the comparison results of incentive mechanisms, the platform can choose the best incentive mechanism with the lowest budget for different area coverage targets.

Our model of the research problem contains three entities: the area, the sensing task, and the user. Each entity can be described by its behavior and/or its relationship with other entities:

- The area entity is modeled according to the Manhattan model as a grid of cells without loss of generality for incentive mechanism studies. The grid has a uniform distribution of cost for traveling across adjacent cells, and no missing cells within. The area represents the types of roads that users may encounter and the varying costs of traveling with different pavement conditions. Meanwhile, the area has another constraint for users. Users can only move horizontally or vertically in one step at a time.

- The sensing task entity contains information on the location of interest and the monetary incentive associated with user participation. The sensing tasks specify roads where pavement sensing is needed.

- The user entity represents users participating in the crowdsensing. As users continue to participate and collect and report data for rewards, they accumulate monetary rewards and endure operation costs.

4 Incentive Mechanism Solutions

Modularity and scalability are critical features needed in designing a crowdsensing framework for deploying and testing incentive mechanisms. Without these features, it would be difficult to swap incentive mechanisms and evaluate them. Our crowdsensing platform and incentive mechanism designs are guided by evaluation metrics described in this section.

4.1 Notations

The symbols we use in this report are shown in Table 1. Two important variables in our model are s_j and u_i. They represent identification numbers of the sensing tasks and users. The tasks s_j and the users u_i respectively have attributes $< u_i, R_{ij}, x_j, y_j >$ and $< s_j, a_i, C_{ij}, x_i, y_i >$. For users, if s_j is 0 or -1, then the user is currently not participating because the user has not selected a sensing task or has dropped out. For sensing tasks, if u_i is 0 then the sensing task has not been assigned to a user. In addition, if a sensing task has a reward equal to 0 then its reward has been claimed.

Table 1: Common Symbols

Symbols	**Meanings**
a_i	Accumulated reward of user u_i
Avg_j	Average distance from task s_j to all users
B	Budget for the platform
BR	Base reward
b	The side length of the grid
C_{ij}	The travel cost for user u_i to complete task s_j
CR	The reward of the task that offers MP
$d_{j,uc}$	Distance from s_j to uc
$d_{j,tc}$	Distance from s_j to tc
IM	Incentive mechanism
k_i	The ranking number for u_i
MP	Maximum profit for user u_i
NPM	Net profit margin
P	Area coverage percentage
P_{ij}	Profit for u_i of sensing task s_j
PC	The platform cost
R_{ij}	Reward of the sensing task s_j for user u_i
(S) s_j	(Set of) Sensing task/ID
S_a	The set of available tasks
SID	The index of task selected by user u_i
s_r	The percentage of trials succeed
T	Threshold for net profit margin
tc	The center of locations of sensing tasks
t_f	Total operation time
(U) u_i	(Set of) User/ID
uc	The center of locations of users
x_i	x-coordinate
y_i	y-coordinate

4.2 Evaluation metrics

The purpose of the evaluation metrics is to offer a means of differentiating the incentive mechanisms and to guide the design of the crowdsensing solutions. The simulations for incentive mechanism evaluations consist of an extensive number of trials. In each trial, we initialize the tasks and users at the beginning and the simulation runs until all tasks are completed or all users drop out. The details of the evaluation metrics are described as follows:

- The total operation time t_f represents the duration of a trial. In one trial, a timer starts from time 0 and ends at the time t_f when all sensing tasks are completed or all users drop out. While two incentive mechanisms may have an equal success rate s_r, one incentive mechanism might have less total operation time t_f. This implies that users have been incentivized to select and perform tasks in efficient ways.

- The platform cost (1) is the amount of money that the platform pays the users through sensing task rewards. The *surplus* is the portion of the budget that is not used by the end of a trial. A lower platform cost reflects the ability of incentive mechanisms to reduce the cost for sensing task rewards.

$$PC = B - surplus. \tag{1}$$

4.3 Platform-driven greedy algorithm

The platform-driven greedy algorithm that we use to design our incentive mechanisms is shown in Algorithm 1. The idea of this algorithm is to select an available task that gives the maximum profit to the user. Thus, this platform-driven greedy algorithm computes the profit of task s_j to user u_i by (2).

$$P_{ij} = R_{ij} - C_{ij} \tag{2}$$

in which R_{ij} is determined by the incentive mechanisms. We will describe more details of R_{ij} in the next subsection. After this algorithm finds out the task s_i which can provide the maximum profit for user u_i, the user u_i needs to check if the net profit margin of the task s_i is greater than the threshold T. If positive, the user u_i selects the task; otherwise, the user u_i drops out.

4.4 Incentive mechanisms

There are 9 incentive mechanisms studied in this report. The task-reverse-auction (TRA) incentive mechanism has been discussed in the literature [15–17]. It is known that the task-reverse-auction incentive mechanism cannot guarantee that all tasks are completed within a short total operation time in untruthful bid scenarios [16]. Our incentive mechanism design has a goal to reduce the total operation time. Thus, we will compare their total operation times in Section VI. The other 8 incentive mechanisms are described as follows.

4.4.1 Static Uniform (SU) incentive mechanism

In static uniform incentive mechanism [12], the incentives of sensing tasks are fixed values that are uniformly distributed and have the value R_{ij} calculated by (3). In this case, R_{ij} is set to the base reward BR.

$$R_{ij} = \frac{B}{|S|} = BR \tag{3}$$

Algorithm 1: Platform-driven greedy algorithm

```
Input: u_i, S_a, T where u_i =< s_j, a_i, C_ij, x_i, y_i >
Output: Updated u_i.s_j
if S_a == ∅ then
    u_i.s_j = −1 // user u_i drops out as no task is available
    return
MP = −∞, CR = −∞
for s_j in S_a do
    P_ij = R_ij − C_ij
    if P_ij ≥ MP then
        MP = P_ij
        CR = R_ij
        s = s_j
if u_i.a_i == 0 then
    NPM = 100 × (MP+CR)/CR
else
    NPM = 100 × (MP+u_i.a_i)/(u_i.a_i)
if NPM < T then
    u_i.s_j = −1 // u_i drops out as no task gives ample profit
    return
u_i.a_i = u_i.a_i + CR
u_i.s_j = s
return
```

4.4.2 Dynamic Relative (DR) incentive mechanism

The incentives change their values R_{ij} based on the distance from currently unavailable users and the user u_i to the sensing task s_j. This incentive mechanism ranks the currently unavailable users and user u_i by their distance to the sensing task s_j in an increasing order. Then, the value of incentive for the sensing task s_j can be calculated by (4).

$$R_{ij} = \begin{cases} BR & k_i = 1 \\ BR(1 - \frac{1}{2}\frac{k_i}{|U|}) & k_i \geq 2 \end{cases} \tag{4}$$

4.4.3 Dynamic/Static User Centric (DUC/SUC) incentive mechanisms

First, the center of user locations is calculated by (5). Then we compute the distance $d_{s,uc}$ from the task s to the user center by (6). The value R_{ij} is inversely proportional to the distance as shown in (7).

- Static case: rewards of sensing tasks are computed only once at the beginning of each trial.
- Dynamic case: it is similar to the static case, but the only difference is that the calculation repeats whenever a user is about to select a sensing task.

$$(x_{uc}, y_{uc}) = (\frac{\sum_{i\in U} x_i}{|U|}, \frac{\sum_{i\in U} y_i}{|U|}) \tag{5}$$

$$d_{s,uc} = |x_s - x_{uc}| + |y_s - y_{uc}| \tag{6}$$

$$R_{ij} = BR(1 - \frac{1}{2}\frac{d_{s,uc}}{b*2}) \tag{7}$$

4.4.4 Dynamic/Static Task Centric (DTC/STC) incentive mechanisms

First, the center of user locations, i.e. tc, is calculated by (8). Then we compute the distance $d_{s,tc}$ from the sensing task s to the sensing task center by (9). The value R_{ij} is inversely proportional to the distance as shown in (10).

- Static case: rewards of sensing tasks are computed only once at the beginning of each trial.
- Dynamic case: it is similar to the static case, but the only difference is that the calculation repeats whenever a user is about to select a sensing task.

$$(x_{tc}, y_{tc}) = (\frac{\sum_{s\in S} x_s}{|S|}, \frac{\sum_{s\in S} y_s}{|S|}) \tag{8}$$

$$d_{s,tc} = |x_s - x_{tc}| + |y_s - y_{tc}| \tag{9}$$

$$R_{ij} = BR(1 - \frac{1}{2}\frac{d_{s,tc}}{b*2}) \tag{10}$$

4.4.5 Dynamic/Static Pit (DPIT/SPIT) incentive mechanisms

In this pit-based incentive mechanism, we use all the users' coordinates to calculate an average distance to the sensing task s by (11). Then, we compute the incentive R_{ij} of the sensing task s by (12).

- Static case: rewards of sensing tasks are computed only once at the beginning of each trial.
- Dynamic case: we need to recalculate the incentives when a user is about to select a sensing task.

$$avg_s = \frac{\sum_i(|x_s - x_i| + |y_s - y_i|)}{|U|} \tag{11}$$

$$R_{ij} = \frac{BR}{2}(1 + \frac{avg_s}{b*2}) \tag{12}$$

5 Simulation Settings

5.1 Parameters

The parameter tuple for each trial is $< B, P, IM >$. After simulations, the evaluation metric tuple $< t_f, PC >$ will be averaged across the total number of simulation trials. In our simulation, the unit of time and money are time unit and fiat unit. Here is the description of the parameters of the experiments:

- Budget B represents the quantity of money that allow the platform to use in a trial. For this experiment, 100 data points were collected in the interval $B \in [100.00, 1090.00]$ with 10.00 spacing between each data point.
- Area coverage percentage P represents the percentage of the area that requires sensing data. Similar to the budget, 100 trials were conducted such that $P \in [20.0\%, 79.4\%]$ and that there was 0.6% spacing between each data point. This interval represents a wide range of possible target percentages for pavement crowdsensing. Note that we round down the area coverage percentage when calculating the number of tasks.
- The final parameter is the incentive mechanism IM used in the trial. The different IM calculate rewards of tasks differently.

5.2 Simulation execution

Given $< B, P, IM >$, the construction phase initializes the numbers of cells, users, and sensing tasks in the following order:

- For each cell, any references to users or sensing tasks are cleared.
- For all users, s_j, a_i, C_{ij}, x_i, and y_i are initialized. s_j is set to 0. Each user would be placed in a cell randomly without overlapping.
- For all sensing tasks, u_i, R_{ij}, x_j, and y_j are initialized. u_i is set to 0. Each sensing task will be placed in a cell randomly with no overlap between other sensing tasks.

In the execution phase, available users start their turns by selecting and committing to a sensing task based on Algorithm 1. Then, the user will update its s_j. In turn, the user information associated with the sensing task s_j will be updated to reflect that the user u_i now performs task s_j. If no suitable sensing task is found, then the user drops out of the trial for all future turns. Unavailable users are the ones who have not dropped out and are committing their turns by moving towards their sensing tasks. If the user lands on the sensing task, then a_i increases by R_{ij}. If the user is not on the sensing task, then the user must wait another turn to move closer. In both cases, C_{ij}, x_i, and y_i are updated to reflect the current user location.

6 Results

Incentive mechanisms are evaluated and compared in three scenarios corresponding to low, medium, and high area coverage percentages for pavement crowdsensing with different numbers of users. The platform cost is used to order the incentive mechanisms based on their performance data as shown in the following figures. The minimal budgets shown in the figures are the lowest budgets that can realize a 100% success rate for the targeted area coverage percentage. It means that any budgets higher than this value allow the platform to achieve the 100% success rate for the targeted area coverage.

6.1 Platform cost comparison

In this subsection, we discuss the comparison of incentive mechanisms in terms of the platform cost.

- Given 25% area coverage, Fig. 1 shows that the SU and DR incentive mechanisms respectively have the lowest platform costs when the platform has 3 users and 15 users. Apart from this, the static and dynamic pit incentive mechanisms always rank among the top three incentive mechanisms in all scenarios.

- Given 50% area coverage, Fig. 2 shows that static and dynamic pit incentive mechanisms still have the best performances of the platform cost in all scenarios. Even though the DTC incentive mechanism achieves the lowest platform cost in *50% area coverage with 45 users*, this observation does not conflict with the previous statement.

- Given 75% area coverage, Fig. 3 shows that SPIT and DPIT always have the lowest platform cost regardless of how many users the platform has.

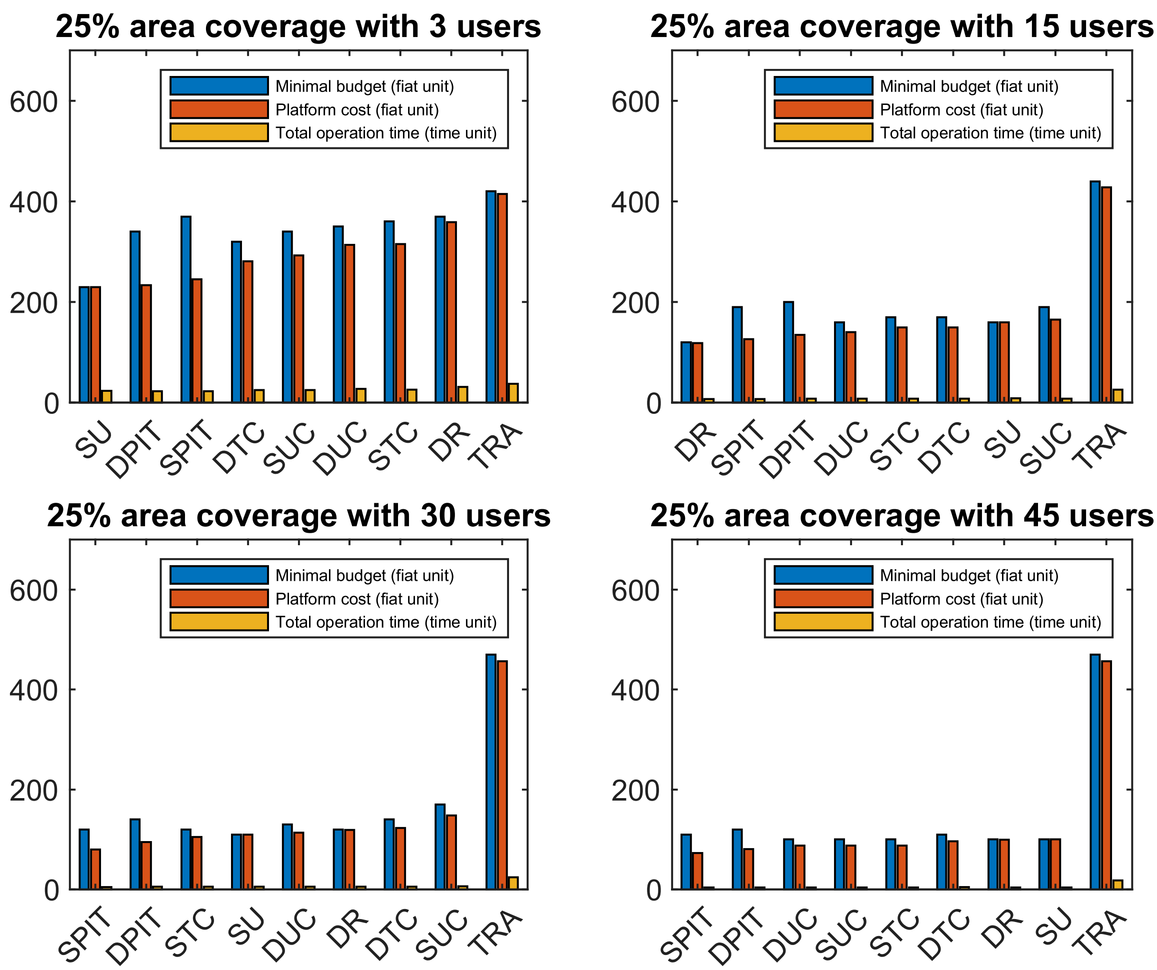

Figure 1: Incentive mechanism comparison: 25% area coverage

Based on the observations described above, we can conclude that SPIT and DPIT are two incentive mechanisms that have the lowest platform cost.

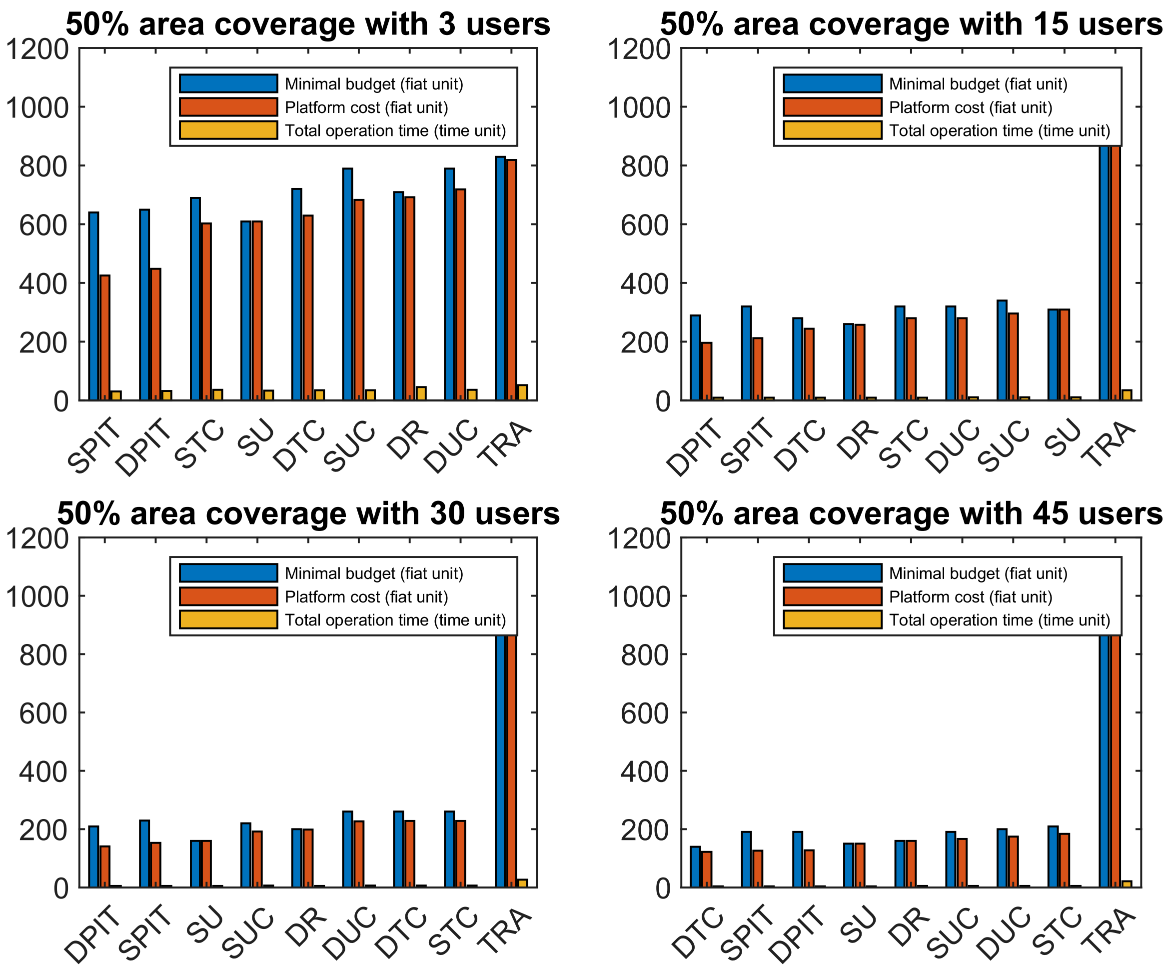

Figure 2: Incentive mechanism comparison: 50% area coverage

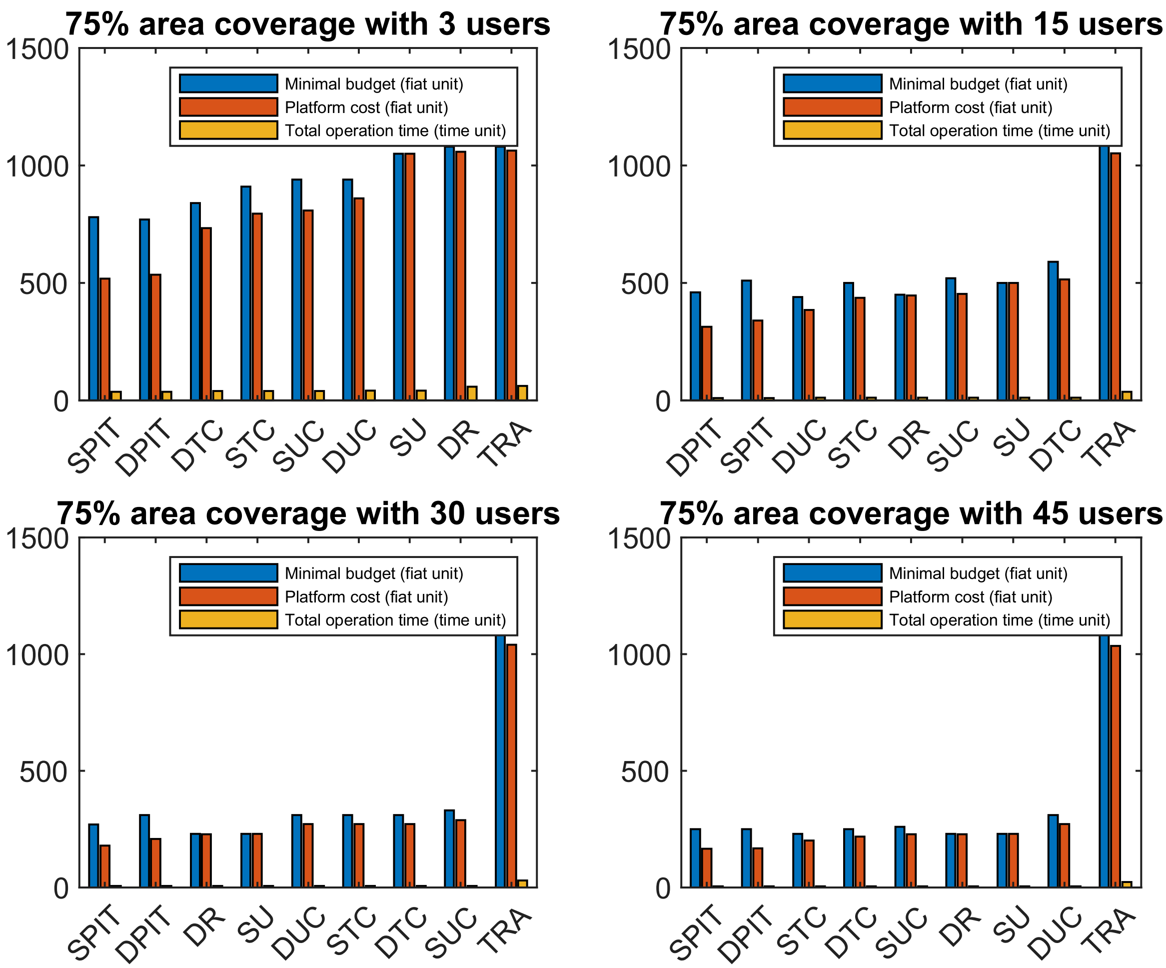

Figure 3: Incentive mechanism comparison: 75% area coverage

6.2 Total operation time comparison

In this subsection, we discuss the comparison of incentive mechanisms in terms of the total operation time. From Figs. 1, 2, and 3, the total operation time of the task-reverse-auction (TRA) incentive mechanism is nearly twice as the total operation times of ours. Additionally, the total operation time of the TRA incentive mechanism becomes longer as the number of participatory users increases while the total operation times of our incentive mechanisms would decrease in the same situation. Therefore, this result proves that our incentive mechanisms have much less total operation time than the task-reverse-auction (TRA) incentive mechanism.

7 Conclusion and Future Work

In this report, we proposed eight incentive mechanisms based on a platform-driven greedy algorithm to help the crowdsensing platform motivate users to collect pavement condition data. Since our incentive mechanisms allow users to select the sensing tasks based on a platform-driven greedy algorithm before they start to collect the data, they can avoid the cost explosion problem observed in the data-reverse-auction incentive mechanisms. From the simulation results, we find that SPIT and DPIT are the incentive mechanisms that have the lowest platform cost. Compared with the task-reverse-auction incentive mechanism, our incentive mechanisms reduce the total operation time by half. Our future research includes large-scale simulations and real-life experiments by extending our prototype pavement crowdsensing system.

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