Incentive mechanism design for citizen reporting application using Stackelberg game

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Article Info

ABSTRACT

The growing utilization of smartphones equipped with various sensors to collect and analyze information around us highlights a paradigm called mobile crowdsensing. To motivate citizens' participation in crowdsensing and compensate them for their resources, it is necessary to incentivize the participants for their sensing service. There are several studies that used the Stackelberg game to model the incentive mechanism, however, those studies did not include a budget constraint for limited budget case. Another challenge is to optimize crowdsourcer (government) profit in conducting crowdsensing under the limited budget then allocates the budget to several regional working units that are responsible for the specific city problems. We propose an incentive mechanism for mobile crowdsensing based on several identified incentive parameters using the Stackelberg game model and applied the multi-objective optimization problem (MOOP) to the incentive model in which the participant reputation is taken into account. The evaluation of the proposed incentive model is performed through simulations. The simulation indicated that the result appropriately corresponds to the theoretical properties of the model.

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1. INTRODUCTION

The increase in the urban population in Indonesia increases the complexity of city problems. As a developing country, cities in Indonesia face a vast amount of problems, from small-scale and simple issues such as trash collection to large-scale and complex problems such as economic development. To solve the various city issues effectively, the cooperation between citizens and the government is required [1]. The utilization of smartphones in terms of mobile crowdsensing enables such a cooperation where the citizens provide information regarding the city issues, while the government collects and analyzes information to gain insights of the various city issues which could then be used for city planning as well as its policies. Figure 1 shows the basic crowdsensing system that consists of a crowdsourcer referred to the government and the participants using their smartphones to perform the sensing service. Both of them are connected via the cloud.

To motivate citizens' participation in crowdsensing and compensate them for their resources, such as battery consumption and data transmission costs, it is necessary to incentivize the participants for their sensing service. Previous studies have contributed to the development of the incentive mechanism on mobile crowd-

sensing, such as the proposed model on the resource-aware incentive mechanism [2], two credit-based privacy-aware incentive schemes [3], and the simple endorsement web to incentivize the participants [4]. Nevertheless, the challenges to incentivize the crowdsensing participant remain open as discussed in [5].

In addition to the challenges to incentivize the participant, another challenge is to optimize crowdsourcer (government) profit in conducting crowdsensing under the limited budget then allocates the budget to several regional working units that are responsible for the specific city problems. For instance, the environmental working unit is responsible for the environmental problems in the city. To address this issue, we propose the multi-objective optimization problem (MOOP) [6] to design an incentive mechanism for mobile crowdsensing regarding the city issues.

To design an incentive model, one can model the interaction between participants and a crowdsourcer as a Stackelberg game model. Under this model, the crowdsourcer as the leader moves first and decides its strategy; then, the participants as followers pick their best response strategy according to the leader strategy, whereas the objective of both the leader and followers is to maximize their utility. There are several studies that used the Stackelberg game to model the incentive mechanism [4], [7]-[13]; however, those studies did not include a budget constraint for limited budget case.
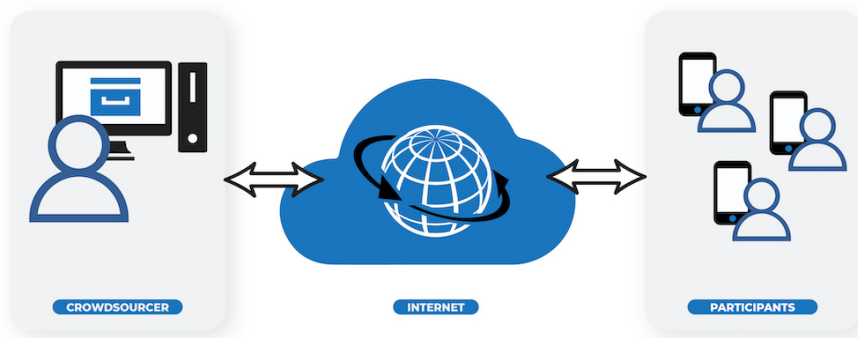

Figure 1. Mobile crowdsensing system

2. RELATED WORKS

There are many studies concerning incentive mechanism design for mobile crowdsensing [14] from multi-armed bandit to game theoretical approaches. Gao *et al.* [15] studied an unknown worker recruitment process as a combinatorial multi-armed bandit problem to determine the recruiting strategy that maximizes the weighted sum of the completion qualities under a limited budget. Wu *et al.* [16] proposed a context-aware multi-armed bandit incentive mechanism to facilitate quality-based worker selection. Auction games to design incentive mechanisms are also widely used. Jin *et al.* [17] designed an incentive mechanism based on the single-minded reverse combinatorial auction to preserve the privacy of the worker's bid against the other honest-but-curious workers. Jin *et al.* [17] proposed the user-centric model auction-based incentive mechanism which is computationally efficient, individually rational, profitable, and truthful. Liu *et al.* [18] proposed IMRAL, i.e., an incentive mechanism based on reverse auction for location-aware sensing, to enhance the willingness of users to participate in crowdsensing by maximizing their expected profits. Another game theoretical approach used in constructing incentive mechanisms is the Stackelberg game [4], [7]-[13].

Previous work by [7] provided an efficient algorithm to compute the unique Stackelberg equilibrium at which the crowdsourcer utility is maximized. The extension of this work is provided by [8], [19] to include privacy considerations and spatial coverage of the collected dataset. However, the optimization of the crowdsourcer utility in these previous works is less relevant for the case when we want to optimize the profit of several regional working units simultaneously. In this case, the notion of multiple crowdsourcers is more appropriate. A study by [20] provided an incentive mechanism with multiple crowdsourcers but did not include the budget constraint. In addition, all of these studies did not consider the participant reputation.

Our work on the incentive model is related to the model provided by [7], [8], [19], [20]. We extend the existing models by taking the multiple crowdsourcers into account, where each of those represents a certain

issue category and thus relates to the regional working unit, and by imposing a budget constraint on the model since it is more relevant in real situations. The multiple crowdsourcers case with the budget constraints allows us to apply multi-objective optimization [21], [22] by considering multiple crowdsourcer objective functions so that we can optimize the profit or utility of each regional working unit simultaneously under a given budget.

3.   SYSTEM MODEL AND PROBLEM FORMULATION

In this study, we designed an incentive mechanism as follows:
- It classifies incentives according to issue categories.
- It considers the participant's reputation and encourages the participant to report the prioritized issues at a certain period.
- For a given allocated budget, it maximizes the utility of both the participant and the government in each category of the issue which corresponds to the regional working unit.

3.1.   System model

The crowdsensing system consists of N participants and a single crowdsourcer (government) who categorized issues into M categories. For instance, there are 17 issue categories as mention in [23] Let $P = \{1, 2, \cdots, N\}$ be the set of participants and $C = \{c_1, c_2, \cdots, c_M\}$ be the set of issue categories where $N, M \geq 2$. In this study, we apply a crowdsourcer-centric model [7], [8], [19], [20]. We use Figure 2 to represent the system.
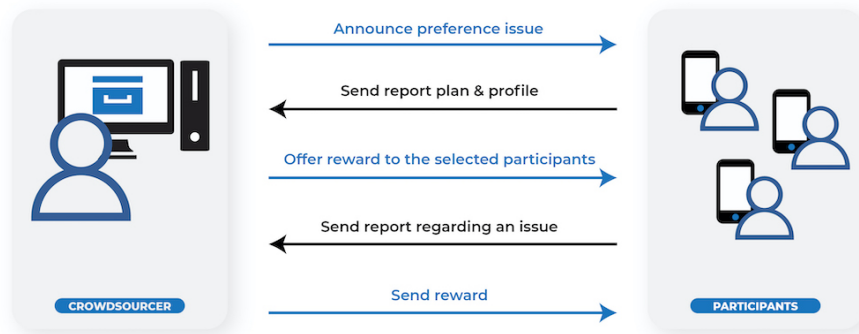

Figure 2. Interaction between participant and crowdsourcer in the incentive model

The crowdsourcer first announces m prioritized (preference) issues $c_p \in C$, $m \geq 1$. The participant i subsequently makes its report plan consisting of the category of issue $c_i \in C$ that he/she wants to participate in and the associated cost per bit of data $\kappa_i \in (0, \kappa_{max}]$ and then submits it to the crowdsourcer. In this case, the participant is free to choose whether he/she wants to report the issue in the prioritized category or another issue that he/she encounters. For instance, if the participant wants to report the broken bridge in his/her town, he/she can select the infrastructure issue in the set of issue categories. We assume that participants are rational and noncooperative, i.e., each participant is only interested in maximizing its utility and if there is not a sufficient reward for reporting an issue, he/she will not contribute in crowdsensing. For each participant, the crowdsourcer knows its profile in terms of its reputation, which is elaborated later. The collection of data (issue category, cost, and reputation) provided by each participant enables the system to compute the optimal set of participants that maximizes the utility of both the participant and the crowdsourcer. The selected participant from the optimal set is then offered some reward for some amount of quality of report q_i that he/she is expected to submit; otherwise, it would affect his/her reputation. After submitting the data, the selected participant receives the payment. In this case, the report quality is determined by the size of the content type of the report, such as the breadth of description, in which we might analyze the details of the text description, and the image resolution or video frame rate and its resolution, in which we might analyze the field of view from an event in a report [24].

We apply the *Stackelberg game* to model the incentive mechanism. In this case, the crowdsourcer is a *leader* and the participants are *followers*. The crowdsourcer and participants are *players* of the game. Each player has its own strategy. The crowdsourcer's strategy is the reward for each category of issues, denoted by $\mathbf{R} = (R_{c_1}, R_{c_2}, \cdots, R_{c_M})$, whereas the strategy of the participant i is the quality of report $q_i \geq 0$ of an issue category that he/she has an interest in participating. The crowdsourcer moves first and decides its strategy in terms of reward $\mathbf{R}$. The participants then pick their best response strategy of the quality of the report on a certain issue to maximize their own utility.

We assume that the reward received by participant i is proportional to q_i, its reputation γ_i, and the parameter associated with the prioritized issue for participant i, denoted by α_i. Let V_p be the set of participants that report the issue on the prioritized category and $\alpha \in (0, 1)$; then, α_i is defined by

$$\alpha_i = \begin{cases} \alpha, & \text{if } i \in V_p \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

which provides more reward for the participant who reports the issue on the prioritized category to motivate sending the report on the prioritized issue. The reputation of participant i, denoted by γ_i, is defined by

$$\gamma_i = \begin{cases} 1, & \text{for new participant} \\ \frac{\text{number of approved reports}}{\text{number of selected report plans}}, & \text{otherwise.} \end{cases} \tag{2}$$

in which $\gamma_i \in [\gamma_{min}, 1]$ and γ_{min} is the minimum reputation required for a participant to contribute in the crowdsensing. We define a new participant as the participant who is just active in crowdsensing for the first p times. Suppose $p = 4$; then, the reputation of the participant is 1 when he/she contributes to crowdsensing in the first four times. In this case, the reputation of the new participant is assigned to the maximum value to provide the opportunity for a new participant to contribute in the crowdsensing. We assume that in the first p times, there is at least one report plan from the new participant to be selected. For other participants, γ_i is proportional to the number of approved reports. The approved report is the report that provides a satisfactory representation of an event/issue from the analysis of its content. The participant whose report plan is selected but does not send the report or its report has a poor representation of the event/issue will gain a lower reputation than the participant whose report is approved.

We refer the utility function of the participant to [7], [8] which assume that the reward is proportional to q_i and the cost function is linear for participant utility. The utility function (i.e., reward minus cost) of the participant i interested in reporting an issue on category c_j is given by the following (3)

$$u_i = \frac{(1 + \alpha_i)\gamma_i q_i}{\sum_{k \in V_j} \gamma_k q_k} R_{c_j} - \kappa_i q_i \tag{3}$$

where R_{c_j} is the reward of issue category c_j and V_j is the set of participants that report an issue on category c_j. The utility function of the crowdsourcer for each category of the issue is

$$u_{c_j} = \lambda \ln \left(1 + \sum_{i \in V_j} q_i^y\right) - R_{c_j} \tag{4}$$

with the constraints

$$\sum_{c_j \in C} (1 + \alpha_{c_j}) R_{c_j} \leq R_{budget} \tag{5}$$

and

$$R_{c_j} \geq 0 \text{ for } c_j \in C \tag{6}$$

where $\lambda > 1$ is a system parameter, $y \in (0, 1)$ is the rate of the crowdsourcer's diminishing return on the participant's quality of the report, whereas the $\ln$ term reflects the crowdsourcer's diminishing return on the number of participants. $\alpha_{c_j} = \alpha$ for the prioritized category; otherwise, it is zero. R_{budget} is the government allocated budget to conduct the crowdsensing. Constraint (5) tells us that the total reward of each issue category is at most as much as R_{budget} in which the term $(1 + \alpha_{c_j})$ provides the additional allocation reward for the prioritized issues. It is obvious that R_{c_j} is nonnegative, as given by constraint (6).

3.2. Optimization problem formulation

The objective of the crowdsourcer is to maximize its utility for each category of the issue for a given allocated budget by determining the optimal reward $\mathbf{R} = (R_{c_1}, R_{c_2}, \cdots, R_{c_M})$, whereas the participant assigns the amount of q_i to maximize its utility after committing to report an issue on category c_j. The Stackelberg game optimization problem can be written as follows:

- Let λ, y, α_{c_j}, and R_{budget} be given. For each category of issue, the crowdsourcer aims to

$$\underset{\mathbf{R}}{\text{maximize}} \quad u_{c_j} = \lambda \ln \left(1 + \sum_{i \in V_j} q_i^y \right) - R_{c_j}, \forall c_j \in C,$$

$$\text{subject to} \quad \sum_{c_j \in C} (1 + \alpha_{c_j}) R_{c_j} \leq R_{budget}, R_{c_j} \geq 0. \tag{7}$$

- Let α_i, κ_i, R_{c_j}, γ_i, γ_{-i}, and q_{-i} be given. γ_{-i} and q_{-i} are the set of reputation and quality reports other than that of participant i, respectively. For a certain issue category c_j, the participant aims to

$$\underset{q_i}{\text{maximize}} \quad u_i = \frac{(1 + \alpha_i) \gamma_i q_i}{\sum_{k \in V_j} \gamma_k q_k} R_{c_j} - \kappa_i q_i,$$

$$\text{subject to} \quad q_i \geq 0. \tag{8}$$

4. PROBLEM RESOLUTION

The objective of both the crowdsourcer and the participant leads to the notion of the Stackelberg equilibrium, i.e., the equilibrium such that no player can increase its utility by unilaterally changing its strategy which is associated with the pair of $\mathbf{R}$ and $\mathbf{q} = (q_1, q_2, \cdots, q_n)$ that maximizes the utility of both the crowdsourcer and the participant for a given category of issue. We solve the Stackelberg game problem in the previous section by using backward induction where the crowdsourcer considers all possible best responses of the participants (if they exist), i.e., the strategy that maximizes each of the participant's utility on a certain issue category regardless of the strategy of other participants; then, the leader chooses its strategy that maximizes its utility according to that knowledge. The best response of the participant after choosing a certain issue category is its strategy at Nash equilibrium, which is defined as follows:

Definition 1 For an issue category, a set of strategies $\mathbf{q}^{ne} = (q_1^{ne}, q_2^{ne}, \cdots, q_n^{ne})$ is a Nash Equilibrium (NE) if for any participant i in that category

$$u_i(q_i^{ne}; q_{-i}^{ne}) \geq u_i(q_i; q_{-i}^{ne})$$

for any $q_i \geq 0$.

q_{-i}^{ne} denotes the set of quality of reports at NE other than q_i^{ne}. In fact, under this model, the strategy at Nash equilibrium of a participant i that commits to report an issue on category c_j exists and is unique [7], [8] which is given by (9):

$$q_i^{ne} = \begin{cases} 0, & \text{if } i \notin S_j \\ \frac{(|S_j|-1)(1+\alpha_i)R_{c_j}}{\gamma_i \sum_{m \in S_j} \frac{\kappa_m}{\gamma_m}} \left(1 - \frac{(|S_j|-1)\frac{\kappa_i}{\gamma_i}}{\sum_{m \in S_j} \frac{\kappa_m}{\gamma_m}}\right), & \text{otherwise} \end{cases} \tag{9}$$

provided by (10),

$$\frac{\kappa_i}{\gamma_i} < \frac{\sum_{m \in S_j} \frac{\kappa_m}{\gamma_m}}{|S_j| - 1}, \text{ for } i \in S_j \tag{10}$$

where S_j is the set of participants such that its report plan is selected on issue category c_j and $|S_j| \geq 2$.

The algorithm to compute the strategy of the participant at Nash equilibrium is provided in [7], [8]. Since we differentiate the participants based on the issue category he/she has chosen, i.e., whether it is a prioritized issue or not characterized by a factor α, we take the parameter prioritized category α_i into account in the calculation of the report quality at NE given by algorithm 1. By applying (9) in the calculation, the report quality at NE of the participants choosing the prioritized issue differs by a factor $(1+\alpha)$ from those who choose the nonprioritized issue category. The crowdsourcer expects a higher report quality for participants who are interested in reporting the issue in the prioritized category than those who report the nonprioritized issue. If

there is a case in which only one participant sends the report plan to a certain issue category, the crowdsourcer might set an arbitrary value of q_i, for instance, $q_i = 1$; then, the participant's utility is $(1 + \alpha_i)R_{c_j} - \kappa_i \approx (1 + \alpha_i)R_{c_j}$ given by $\kappa_i \ll (1 + \alpha_i)R_{c_j}$ [20].

Algorithm 1 Compute the report quality at Nash Equilibrium

1: Set of issue categories $C = \{c_1, c_2, \cdots, c_M\}$
2: Set of prioritized categories $C_p \subset C$
3: **for each** $c_j \in C$ **do**
4:    For all participants in issue category c_j, set $\alpha_i = \alpha$ if $c_j \in C_p$. Otherwise, set $\alpha_i = 0$.
5:    Sort n participants such that
   $\frac{\kappa_1}{\gamma_1} \leq \frac{\kappa_2}{\gamma_2} \leq \cdots \leq \frac{\kappa_i}{\gamma_i} \leq \cdots \leq \frac{\kappa_n}{\gamma_n}$.
6:    Select two participants with the lowest $\frac{\kappa_i}{\gamma_i}$, i.e.,
   $S_j \leftarrow \{1, 2\}$.
7:    $S_j \leftarrow S_j \cup \{i\}$ for other participant $i \leq n$ as long as $\frac{\kappa_i}{\gamma_i} < \frac{\sum_{m \in S_j} \frac{\kappa_m}{\gamma_m}}{|S_j| - 1}$.
8:    For each participant $i \in c_j$, if $i \in S_j$, then $q_i^{ne} = \frac{(|S_j| - 1)(1 + \alpha_i)R_{c_j}}{\gamma_i \sum_{m \in S_j} \frac{\kappa_m}{\gamma_m}}\left(1 - \frac{(|S_j| - 1)\frac{\kappa_i}{\gamma_i}}{\sum_{m \in S_j} \frac{\kappa_m}{\gamma_m}}\right)$. Otherwise, $q_i^{ne} = 0$.
9:    Obtain the set of report qualities at NE for issue category c_j, i.e., $(q_1^{ne}, q_2^{ne}, \cdots, q_n^{ne})$.
10: **end for**

From (9), we know that there is a unique strategy for each participant to maximize its utility. Therefore, the crowdsourcer can choose the optimal strategy according to his knowledge about each participant's best response. We might rewrite (4) as (11),

$$u_{c_j} = \lambda \ln\left(1 + R_{c_j}^y \sum_{i \in S_j} T_i^y\right) - R_{c_j} \text{ for } c_j \in C, \tag{11}$$

where

$$T_i = \frac{(|S_j| - 1)(1 + \alpha_i)}{\gamma_i \sum_{m \in S_j} \frac{\kappa_m}{\gamma_m}}\left(1 - \frac{(|S_j| - 1)\frac{\kappa_i}{\gamma_i}}{\sum_{m \in S_j} \frac{\kappa_m}{\gamma_m}}\right)$$

In (11) together with (5) and (6) form the multi-objective optimization problem (MOOP). There are many methods for solving MOOP including the weighted sum method [25], ϵ-constraint method [26], and multi-objective genetic algorithm method [27]. In particular, the weighted sum method is widely used for its simplicity. In this study, we use the weighted sum method to solve the crowdsourcer's utility maximization problem. We consider the composite function U as a linear combination of the crowdsourcer's utility function for each issue category given by (12),

$$U = \sum_{c_j \in C} w_{c_j} u_{c_j} \tag{12}$$

where w_{c_j} is a constant, $w_{c_j} > 0$. The weight w_{c_j} is greater for the prioritized issue categories than for those that are not prioritized. We perform function transformation [28] on each crowdsourcer's utility function so that each function has a similar range as (13),

$$u_{c_j}^t = \frac{u_{c_j}}{|u'_{c_j}|} \tag{13}$$

where $u_{c_j}^t$ is transformed u_{c_j}, and $|u'_{c_j}|$ is the absolute maximum of u_{c_j}. The maximum value of u_{c_j} exists provided by (14),

$$\frac{\partial^2 u_{c_j}}{\partial R_{c_j}^2} = -\frac{\lambda y[(1 - y)R_{c_j}^{y-2}P + R_{c_j}^{2y-2}P^2]}{(1 + R_{c_j}^y P)^2} < 0 \tag{14}$$

for $R_{c_j} > 0$, where $P = \sum_{i \in S_j} T_i^y$, which is strictly concave. Moreover, $u_{c_j} = 0$ as $R_{c_j} = 0$ and $u_{c_j} \to -\infty$ as $R_{c_j} \to \infty$.

Now, the problem for maximizing (11) with the constraint given by (5) and (6) has turned into the problem of maximizing the transformed composite function

$$U_t = \sum_{c_j \in C} w_{c_j} u_{c_j}^t \tag{15}$$

with those constraints. The following theorem provides the Stackelberg equilibrium on the model of the Stackelberg game.

Theorem 1: Let $w_{c_j} > 0$ be given, $c_j \in C$. There exists the Stackelberg equilibrium $(\mathbf{R}^*, \mathbf{q}^{ne})$ on the proposed Stackelberg game where $\mathbf{R}^*$ maximizes the crowdsourcer utility for each issue category.

Proof 1: For a given category of issue, we have known from the previous discussion that there exists a unique strategy set that maximizes each participant's utility, i.e., the strategy set at Nash equilibrium. Thus, it suffices to show that $\mathbf{R}^*$ exists. The constraints (5) and (6) form a compact and convex set on $\mathbb{R}^M$, and U_t is continuous on the constraints which guarantees the existence of $\mathbf{R}^*$. In addition, let us consider the second partial derivatives of U_t as (16)

$$\frac{\partial^2 U_t}{\partial R_{c_j}^2} = -\frac{w_{c_j} \lambda y [(1-y) R_{c_j}^{y-2} P + R_{c_j}^{2y-2} P^2]}{|u_{c_j}'|(1 + R_{c_j}^y P)^2} < 0 \tag{16}$$

and

$$\frac{\partial^2 U_t}{\partial R_{c_j} \partial R_{c_k}} = 0 \ \text{ for } j \neq k \tag{17}$$

which form a diagonal Hessian matrix with negative entries so that the Hessian matrix is negative definite. Hence, U_t is strictly concave on its domain. Thus, $\mathbf{R}^*$ is unique for a given $w_{c_j} > 0$ and it is on the Pareto front.

5. SIMULATION RESULTS

For every number of issue category M, we distinguish the issue categories into two categories, i.e., the preference (prioritized) category and nonpreference category. Thus, we might set $M = 2$ and the set of issue categories is given by $C = \{c_1, c_2\}$ in which c_1 is preference category and c_2 is nonpreference category. For each category, the number of participants $N = 1000$. We set parameter $\lambda = 10$ and $y = 0.5$ and perform several simulations by using the CVXPY solver [29] as follows:

- Simulation 1: We let $\gamma_{min} = 0.3$ and $\kappa_{max} = 5$ and assume that the reputation and cost for each participant is randomly uniformly distributed over $[\gamma_{min}, 1]$ and $\kappa_i \in (0, \kappa_{max}]$. We then vary preference parameter α in the range $[0, 1]$ with the increment 0.1. In this case, we solve the trivial optimization problem (not MOOP) by considering an issue category. Figure 3 shows the optimal reward at a certain category increases as the value of α increases. This occurs because increasing α will increase the first term of (11) so that the crowdsourcer utility and the optimal R increase.
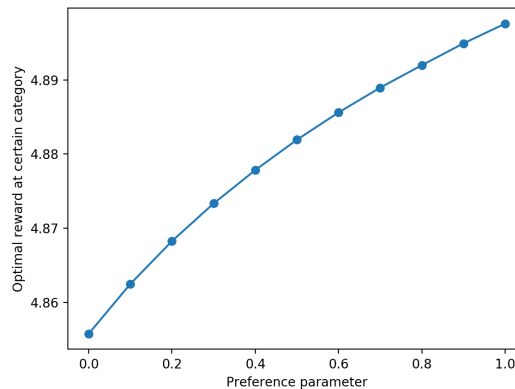

Figure 3. Optimal reward for different preference parameters

- Simulation 2: We let $\alpha = 0.4$. We use similar distribution as in simulation 1 for the reputation and cost of the participant. We plot the pareto front for different $R_{budget} \in [3, 7]$ by an increment of 1 with 1000 data points as shown in Figure 4. Since the budget is limited, the pareto optimal is on $X = \{R_1, R_2 \in \mathbb{R}^2 | (1 + \alpha)R_1 + R_2 = R_{budget}\}$.
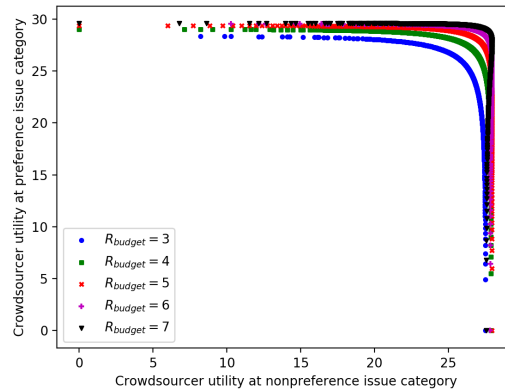

Figure 4. Pareto front for different R_{budget}

- Simulation 3: We let $R_{budget} = 8$ and $\alpha = 0.4$. The reputation and cost distribution of the participant is similar to simulation 1. We vary the weight constant for preference issue category w_{c_1} in the range $[1, 10]$ by an increment of 1, and we set the weight constant for the nonpreference issue category $w_{c_2} = 1$. Thus, the relative weight $\frac{w_{c_1}}{w_{c_2}} = w_{c_1}$. Figure 5(a) represents the graph of the optimal reward of the preference and nonpreference categories of issues for different values of the relative weight. As the relative weight increases, the optimal reward of the preference category increases, but the optimal reward of the nonpreference category decreases as well as the optimal crowdsourcer utility for each category as shown in Figure 5(b). In this case, the budget is more allocated to the prioritized issue as the relative weight increases.
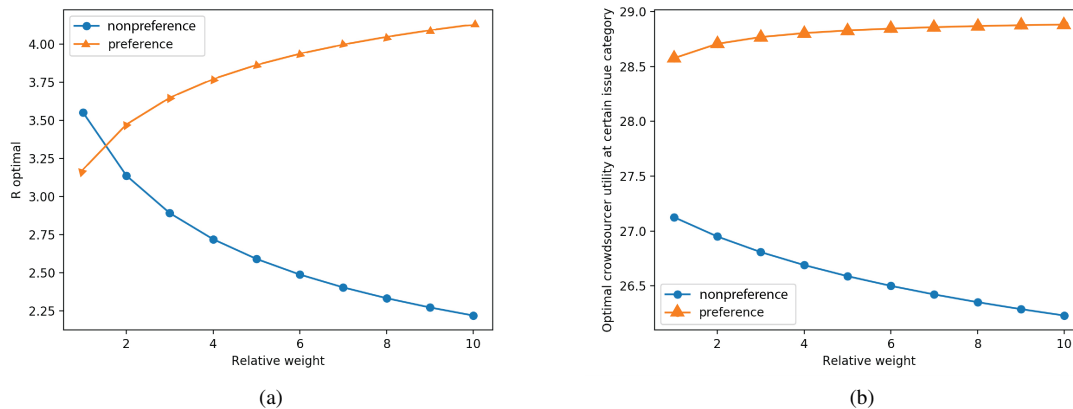

(a)

(b)

Figure 5. The optimal value of (a) reward and (b) crowdsourcer utility of preference and nonpreference issue categories for different relative weights

- Simulation 4: We let R_{budget} be expressed over interval $[1, 15]$ with an increment of 1, $\alpha = 0.4$, $w_{c_1} = 5$, and $w_{c_2} = 1$. The distribution of reputation and cost of each participant is similar to simulation 1. We examine the sum of the report qualities at Nash equilibrium for each category (preference and nonpreference), the sum of crowdsourcer utilities, and the sum of optimal rewards of those categories over the range of R_{budget} given by Figure 6(a) to Figure 6(c), respectively. From these figures, we see that after certain R_{budget} on interval 10 to 12, the sum of report qualities reported at NE, the sum of crowdsourcer utilities, and the sum of optimal rewards start to increase slowly and are almost constant after $R_{budget} = 12$. The reason is

that after certain R^*_{budget}, the reward for each issue category attains its optimal value such that the optimal reward for c_1 and the optimal reward for c_2, denoted by $R^*_{c_1}$ and $R^*_{c_2}$, respectively, satisfy the condition $(1 + \alpha)R^*_{c_1} + R^*_{c_2} \leq R_{budget}$.
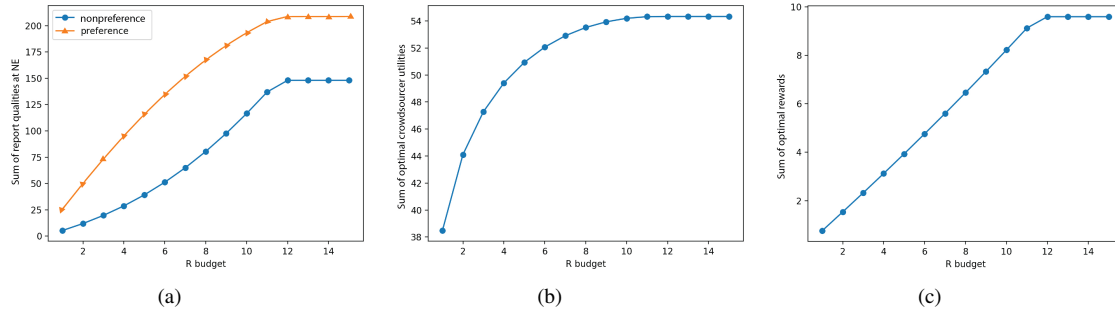

Figure 6. The sum of (a) report qualities at NE, (b) optimal crowdsourcer utilities, and (c) optimal rewards R_{budget}

- Simulation 5: We let $R_{budget} = 10$, $\alpha = 0.2$, $\gamma_{min} = 0.5$, $w_{c_1} = 5$, and $w_{c_2} = 1$. We vary κ_{max} in the range [1,10] with an increment of 1 and assume that the reputation of each participant is randomly uniformly distributed over $[\gamma_{min}, 1]$, whereas its cost is uniformly distributed over $\kappa_i \in (0, \kappa_{max}]$. Figures 7(a) and 7(b) show the sum of report qualities at NE for each category and the sum of crowdsourcer utilities for different κ_{max}, respectively, where these sums decrease as κ_{max} increases as mentioned in [7].
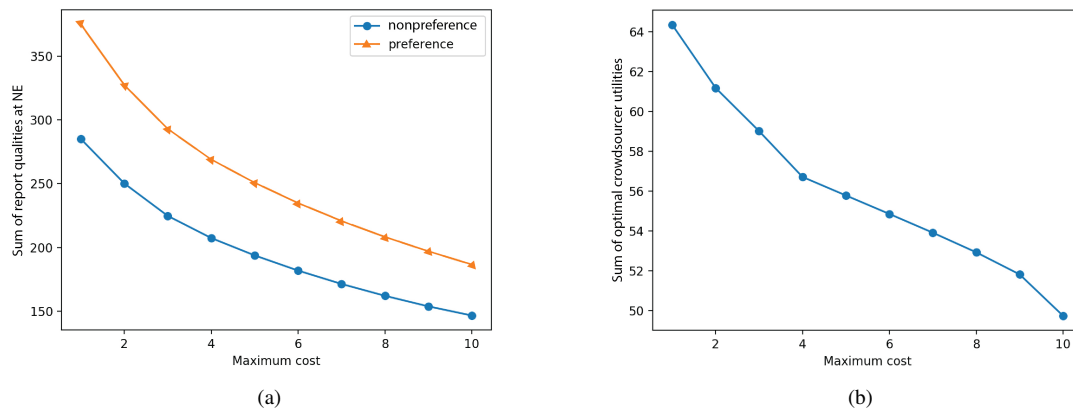

Figure 7. The sum of (a) report qualities at NE and (b) crowdsourcer utilities for different κ_{max}

6. CONCLUSION

In this study, we designed an incentive mechanism for mobile crowdsensing based on several identified incentive parameters using the Stackelberg game model. We designed the incentive mechanism that classified incentives according to the issue categories and motivated participants to report the prioritized issue. In addition, it considered the participant's reputation. We used multi-objective optimization to provide the maximization of the crowdsourcer utility in each category of the issue which corresponds to the regional working unit for a given allocated budget. The simulation indicated that the result appropriately corresponds to the theoretical properties of the model.

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