Maximization of Data Points in Mobile Crowdsensing System: An incentive mechanism for players in cooperative game

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Abstract

Vehicular mobile crowdsensing (MCS) enables a lot of smart city and urban sensing applications, such as smart transportation, environmental monitoring etc. However, many MCS are built on non-dedicated sensing platform, e.g. taxis. The primary goal of these vehicles is not sensing, but to make profits. Therefore to ensure the data quality, MCS based on non-dedicated sensing platforms requires an actuation strategy to collect enough data with limited budget. However, the collaboration between vehicles make it difficult to utilize the limited budget efficiently, for example, the drivers could organize and ask for higher payments. In our project, we propose an incentive mechanism to assign the budget and force the vehicles report their real 'need' monetary reward to help collect data. We show that by using our reward algorithm, the optimal strategy for vehicles maximizes the actuated vehicle number. We also test the algorithm using synthesized data and show the optimality of the proposed incentive mechanism.

1 Introduction

Urban sensing network has been widely used for collecting temporal-spatial data such as air quality and weather conditions. Traditionally, these data are taken by stationary, professional sensors with high accuracy. However, this approach suffers both from high cost and poor geographical coverage due to limited number of sensing stations. Urban mobile sensing network using non-dedicated sensing platform has been gradually adopted to counter this problem. Tiny mobile sensors are mounted on existing moving vehicles to provide flexible, economical temporal-spatial coverage. For example, taxi-based mobile sensing network can monitor the city-wise air pollution; delivery drone-based mobile sensing network can be used for cartography. For example, in taxis-based mobile sensing network, drivers will be asked to open the GPS sensor and vibration sensors in their mobile phone to collect the data during running.

However, with limited budget, the collaboration between these vehicles would affect the data collection of sensing system. These vehicle platforms are not designed for mobile sensing network. The objectives and utility measures of vehicles are different from a data-collection perspective. In general, the crowdsoucer, which is the sensing people, will pay monetary reward to drivers for each task. However, since the vehicle platform provides the convenience for drivers to communicate, drivers always tend to ask for higher reward than a general commuting task. Here the reward for general commuting task means the profits of conveying one passenger in same time slots. With limited budget, higher reward means low number of actuated vehicles, and thus small number of collected data points. In general, few data points will affect efficiency of crowdsensing system and the quality of data provided to data analysis side. For example, in the taxis-based sensing network case, taxi

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drivers tend to collaborate to ask for high monetary reward to collect and upload the data during given time interval. Thus our collected data points could decrease with increasing requested rewards.

Here we plan to design an incentive mechanism to actuate vehicles to achieve optimal sensing quality under limited budget, easing the objective conflict between sensor carriers and sensing network. Challenges to this problem include 1) communication between drivers, 2) budget constraints. Limit budget requires a realistic strategy to control only a subset of carriers while achieving high data quality. Various carriers will have diverse preference in taking actuation assignment. The communication among carriers make it difficult to setup simple customized incentive strategies for different carriers.

To address these challenges, we propose an incentive mechanism to split the collaboration between vehicles and ensure the optimal strategy for drivers to maximize our collected data points. Our algorithm gives the strategy in an online cooperative non-transferable utility game. The game includes multiple rounds. At the beginning of each round, the drivers will report their threshold to accept one task. According to the reported threshold and historical reward information, our algorithm will calibrate the estimation of ground truth threshold to accept one task for drivers. According to the budget constraints, a number of reward will be assigned to selected vehicles. The vehicles could decide to accept the reward and finish the task or not. But this decision will affect the left budget and our estimation for its threshold in the next round. The incentive is a deterministic strategy.

In Section 2, we talked about the related work in mobile crowdsensing and cooperative game. Section 3 formulate the problem and discussed the challenges of mechanism design. Section 4 introduced our proposed incentive mechanism. Section 5 prove the optimality of strategy induced by our incentive mechanism in 2-players multiple rounds game. Then we evaluate the mechanism using synthesized data and give the conclusion.

2 Related Work

Based on the interdisciplinary research field, the related work mainly includes two parts: 1) the research on incentivizing vehicles to truthfully report their demand of reward to finish the tasks in MCS and 2) cooperative game.

2.1 Mobile crowdsourced sensing

Mobile crowdsourced sensing (MCS) is a paradigm that utilize existing pervasive mobile devices to collect data[1, 2]. Users' participation and reliability is very important to ensure the data quality of the MCS application. Most of current practices focus on off-line or non-cooperative scenarios.

Off-line scenario requires user's reliability as known priori. For example, [3] introduced an incentive mechanism in which users sell their sensing data to service provider with their claimed bids, and a service provider selects multiple users and purchases their sensing data. [4] used contract theory to help crowdsoucer decide different task-reward combinations for many different types of users under complete information. [5] modeled the incentive mechanism as a Stackelberg game and designed incentive mechanisms to motivate smartphone users with prior information about users.

Non-cooperative scenario refers that each user makes decision independently without communicating or forming coalitions with other users[6] designed an incentive mechanism such that at the Bayesian Nash Equilibrium of the non-cooperative game, each user maximizes the expected utility only with maximum possible effort. [7] proposed an online auction scheme to incentivize the users in non-cooperative game.

2.2 Cooperative Equilibrium

Nash Equilibrium (NE) assumes that players will make a best response to whatever other players' responses are. However, this assumption does not always hold in cooperative game. Consider the Prisoner's Dilemma, the both prisoners could get best utilities by collaborating with each other if each one commits to corporate. In games where players could collaborate to maximize their utilities, the best strategy assumption of NE can not explain the collaboration behaviour for players. [8] proposed the concept of perfect cooperative equilibrium (PCE) to characterize the cooperative behavior. They defined a strategy profile is a PCE in a 2-player game if each player get utility not smaller than that she get if the other player were best-responding. [9] proposed the coco (cooperative competitive) value which tries to capture the cooperative behavior. This solution decompose every game into cooperative and competitive components, which makes it easier to compute. The coco value needs side payments to be achievable.

3 Problem formulation

In our problem, we assume there are a total number of C vehicles. The actuation will last N rounds. There are $\mathcal{B}$ budget for the total N rounds. At the beginning of each round, vehicle drivers c report his/her threshold T_c to accept one task in current round. The crowdsourcer will select some vehicles to actuate under the budget constraints. After reward assigned, the selected vehicle driver will make decision by themselves to accept the task or not in this round. Since we assume the driver is rational, the vehicle will take the task if the assigned reward exceeds the ground truth threshold of the vehicle. One data point could be collected when one vehicle accepts one task. We assume that the game is a NTU cooperative game. Since when there are many vehicles, it is unrealistic to ensure the utility transferred between drivers in a fair way.

Here we assume that 1) there exists a ground truth threshold $T^\star$ for each vehicle for each round to ensure not losing money, but this threshold is unknown. 2) for each round, the ground truth threshold to accept one task for all vehicles are the same, which means that $T^\star_{1,n} = \cdots = T^\star_{C,n}$ for $\forall n \in \{1, \cdots, N\}$. 3) the ground truth threshold are consistent during all rounds, which means $T^\star_{c,1} = \cdots = T^\star_{c,N}$ for $\forall c \in \{1, \cdots, C\}$. 4) the budget we have could support at least one driver for one task; 5) as long as our reward is not smaller than the ground truth threshold, the driver will take the task.

The objective of crowdsourcer is to design an appropriate incentive mechanism to ensure that after N rounds, the budget is best utilized to actuate as large number of vehicles as possible. The objective of driver is to maximize the total reward after N rounds. Here we write the optimization problem formulation for crowdsourcer in eq.(1)∼(3).

$$\max_{R_{c,n}} \sum_{n=1}^{N} \sum_{c=1}^{C} I(R_{c,n} \geq T^\star) \tag{1}$$

$$s.t. \sum_{n=1}^{N} \sum_{c=1}^{C} R_{c,n} \leq \mathcal{B} \tag{2}$$

$$R_{c,n} \geq 0 \tag{3}$$

The objective function for crowdsourcer is the total number of accepted tasks in Equation (1). $I(\cdot)$ is indicator function. Equation (2) represents the budget constraints, which means the total reward assigned to vehicles after N rounds should not exceed the budget. Equation (3) ensures the reward to each vehicle is positive.

For the vehicle drivers, the objective is to maximize their total reward as shown in Equation (4). If there is a tie, which means multiple strategies exist to obtain maximum reward, the driver will select the one taking least times of task, which means the strategy minimizing the $\sum_n I(R_{c,n} \geq T^\star)$ for vehicle c.

$$\max_{T_{c,1},\cdots,T_{c,N}} \sum_{n=1}^{N} R_{c,n} \tag{4}$$

One characteristic of the NTU cooperative game is that the communication between players provides more information for each player and decreases the uncertainty. Therefore it is possible for the drivers to commit some strategy to maximize all of their rewards without taking respective efforts.The general reward mechanism like assigning threshold to people who reports the minimum threshold will not work well. For example, assume that we have a 2 rounds game, 2 vehicles, budget of 20 units, and the ground truth threshold for one task is 5 for both vehicles and rounds. As a crowdsourcer, to best utilize the budget, we expect that each vehicle will take 5 for each round and thus we could collect 4 data points. However, if using the general reward mechanism assigning threshold to people reporting minimum threshold at each round. The driver could collaborate and report threshold as driver 1:$(10, 50)$ and driver 2:$(50, 10)$. In this way, the driver 1 will get 10 by only accepting one task in the first round, and driver 2 will get 10 by only accepting one task in the second round. So the drivers could collaborate to obtain the maximum reward 10 per person by taking effort of only 1 task. Under this collaboration, we could only collect 2 data points, which means the crowdsourcer will lose the utilities.

4 Incentive mechanism

To achieve the objective of crowdsourcer, we propose an incentive mechanism to introduce the bias between drivers, force drivers to compete with each other and thus split the collaboration. The basic idea here is to 1) avoid paying too much at one round, so we pay at most $\frac{\text{budget left}}{\text{round left}}$ in one round; 2) avoid leaving too large number of payments to final rounds, so if all players report threshold large than upper bound for one round $\frac{\text{budget left}}{\text{round left}}$, we will pay the upper bound reward to one person and see whether he/she will accept it; 3) bias the drivers according to their identification, for example, if two drivers always report the same threshold in all rounds and we can only choose one driver for each round, then we always assign the reward to the first driver in all rounds.

Algorithm 1: Car selection policy

Input : total budget $\mathcal{B}$
number of rounds N
number of cars C
Output : reward $R_{c,n}$ for each car c in each round n

initialize $esti(c, 0) \leftarrow \infty$ for every car c ;
initialize $B_{used} \leftarrow 0$;
broadcast B, N, C ;
for $n \leftarrow 1$ **to** N **do**
    for $c \leftarrow 1$ **to** C **do**
        collect current claimed threshold from car c as $T_{c,n}$;
        $esti(c, n) \leftarrow min(T_{c,n}, esti(c, n - 1))$;
    end
    $R \leftarrow \min\big(\min(esti(c, n)), (B - B_{used})/(N - n + 1)\big)$;
    $K \leftarrow \lfloor (B - B_{used})/(R \times (N - n + 1)) \rfloor$;
    stable sort $esti(c, n)$ in ascending and get the top K car set $selected_n$;
    $R_{c,n} \leftarrow R$ for $c \in selected_n$, otherwise $R_{c,n} \leftarrow 0$;
    for $c \in selected_n$ **do**
        assign task to c with reward $R_{c,n}$;
        if c *accepts task* **then**
            $esti(c, n) \leftarrow R_{c,n}$;
            $B_{used} \leftarrow B_{used} + R_{c,n}$;
        end
    end
end

Algorithm 1 describes the proposed incentive mechanism. Basically, the algorithm firstly calibrates the estimation of driver's threshold $esti(c, n)$ based on the rewards in previous rounds and reported threshold at current round. Then R is obtained by taking the minimum between $\min(esti(c, n))$ and upper bound payment for each round $\frac{\mathcal{B} - B_{used}}{N - n + 1}$, which means that if for all drivers $\min(esti(c, n)) > \frac{\mathcal{B} - B_{used}}{N - n + 1}$, then we will try to pay 1 driver $\frac{\mathcal{B} - B_{used}}{N - n + 1}$ instead of not paying anyone. Then we calculate the number of K drivers we could pay at current round. Top K drivers will be selected from stable ascending sorted $\min(esti(c, n))$ so that drivers who report smaller threshold is more possible to be selected. The drivers who is not selected will be paid 0, which means that they will not accept the tasks. Since we assume the drivers are rational and our threshold will pay the minimum one ever reported, so they would not report a threshold smaller than the ground truth threshold. When all drivers report too large number at the beginning to save budget for later rounds, we will try to pay $R_{c,n}$ to see whether the driver will accept it. Since we assume that if $R_{c,n} \geq T^{\star}$, the driver c will accept the task. If c accepts the task, we will update our estimation on the ground truth threshold as $esti(c, n) = R_{c,n}$.

Overall, the algorithm is deterministic and based on that the drivers could collaborate to report thresholds but decide to take task by themselves. This makes it possible that driver may follow others to report a high number, but take the task even though the reward is smaller than reported number. This also makes sense since all drivers want to maximize their own utility no matter in a cooperative or non-cooperative way.

5 Proof of Optimality

We give a theoretical proof on the optimality of our algorithm for the case of 2 cars and multiple iterations. Our proof is two-fold: first, we show that the desired strategy for the senser side can be obtained if all drivers report their threshold truthfully in each iteration; second, such an honest strategy is also the best possible strategy for each driver, in the sense that it produces an equilibrium for all drivers which maximizes their objective function. The exact definition of equilibrium and maximization will be defined at the beginning of the second part of the proof.

The first part of the proof is straightforward. If the true threshold T^* satisfies $T^* \geq B/NC$, where B is the budget and N the number of iterations, at most $\lfloor B/T^* \rfloor$ cars can be actuated in the game. If each car reports T^* truthfully, it follows from the algorithm that the pay estimated in each round will stay at T^*, by the end of the game the algorithm would have spend all budget to actuate as many cars as possible. Therefore the objective for the senser is achieved.

If the true threshold T^* is smaller than B/NC, the budget is large enough to pay each driver in every iteration. In this case, as long as all drivers report the same threshold, any value of the threshold between T^* and B/NC, inclusive, is acceptable. It is obvious that each round, the number of cars selected $K = C$, and the total number of cars actuated is NC.

It remains to show that our algorithm forces drivers to report the threshold truthfully. To do this, we introduce the notion of *perfect cooperative equilibrium* [8], an equilibrium that describes the best strategy for players in a cooperative game.

Definition 5.1. *Given a two-player game G, a strategy s_i for player i in G is a* ***best response*** *to a strategy s_j for the other player j if s_i maximizes player i's expected utility given that the other player is playing s_j, that is, $U_i(s_i, s_j) = \sup_{s'_i \in S_i} U_i(s_i, s_j)$. Let $BR_i^G(s_j)$ be the set of best responses to s_j in game G. We omit the superscript G from here on as the game is clear from context.*

Definition 5.2. *Given a two-player game G, let BU_i denote the best utility that player i can obtain if the other player j best responds; that is,*

$$BU_i = \sup_{s_i \in S_i, s_j \in BR(s_i)} U_i(s).$$

Definition 5.3. *A strategy profile s is a* ***perfect cooperative equilibrium (PCE)*** *in a two-player game G if for all $i \in \{1, 2\}$, we have*

$$U_i(s) \geq BU_i.$$

The definition of PCE coincides with our commonsense that if a cooperative strategy generates greater or equal utility to each player than that when everyone acts selfishly, then it is a stable and superior strategy that will be favored by all players. We are now ready to show that the honest strategy is a PCE under our algorithm.

***N* = 1**. If $T^* \leq B/2, \forall i,\ BU_i = B/2$ because for any strategy s_i that reports a threshold T less than or equal to $B/2$, any best response of j, $s_j \in BR(s_i)$ will be report at least the same or greater threshold than that of i, which according to our algorithm, will result in both two players receive T in each round. Since this holds for any reported threshold in $[T^*, B/2]$, the total reward will be upper bounded by $B/2$.

In this case, the desired strategy of the crowdsourcer is when all players report a threshold in range $[T^*, B/2]$. Let s be the honest strategy that every player reports a threshold of $B/2$, then we have

$$U_i(s) = B/2 \geq BU_i = B/2$$

for any i. Hence the honest strategy is a PCE in this situation.

Otherwise, $T^* > B/2$. Notice that the situation is asymmetric for player 1 and 2. For player 1, if he reports T^* honestly, any response of player 2 can only be in the range $[T^*, B]$ as any value below the threshold is unacceptable for any player. In this case, no matter which threshold is reported by player 2, as we determine the reward assigned R by the minimal value of the two, $R = T^*$, and as we are using stable sort to select top $K = B/T^* =$ value, only player 1 will be selected. But if player 1 reports a threshold $T_1 > T^*$, player 2 can best response by reporting any value between $[T^*, T_1]$. In this case, player 1 gets 0 reward. Hence,

$$BU_1 = \sup\{T^*, 0\} = T^*$$

For player 2 and any threshold T_2 reported, player 1 can best reponse by reporting the same threshold $T_1 = T_2$, and because of stable sort, only player 1 will be selected. Therefore

$$BU_2 = \sup\{0\} = 0$$

For the honest strategy, every player reports T^*. We have

$$U_1(s) = T^* \geq BU_1 = T^*$$
$$U_2(s) = 0 \geq BU_2 = 0$$

Therefore the honest strategy is a PCE for any T^* in range $[0, B]$. For the case when threshold greater than B, no player will ever be actuated and the game becomes trivial. Now we are ready to prove that such a result also holds for any $N > 1$.

$\boldsymbol{N > 1}$. First, observe that according to our algorithm, when B, N is fixed and $C = 2$, the truth-telling strategy s produces deterministic total return for each of the two drivers:

$$R_1 = \min(N, \left\lfloor \frac{B}{T^*} \right\rfloor) T^*$$
$$R_2 = \left\lfloor \frac{B - R_1}{T^*} \right\rfloor T^*$$

This follows naturally from the algorithm that when both drivers report the same threshold, driver 1 is always preferred. Therefore driver 1 is actuated as many times as possible, which is $\min(N, \lfloor B/T^* \rfloor)$. Driver 2 gets the leftover part of the budget.

Actually, similar result can be writen for the case when $C > 2$:

$$R_1 = \min(N, \left\lfloor \frac{B}{T^*} \right\rfloor) T^*$$
$$R_2 = \min(N, \left\lfloor \frac{B - R_1}{T^*} \right\rfloor) T^*$$
$$\dots$$
$$R_C = \left\lfloor \frac{B - R_1 - R_2 - \ldots - R_{C-1}}{T^*} \right\rfloor T^*$$

With this result, we prove that the truth-telling strategy s is a PCE by decomposing the problem into 3 cases:

1. $B \leq NT^*$
2. $B \geq CNT^* = 2NT^*$
3. $NT^* < B < 2NT^*$

Case 1. $B \leq NT^*$.

For the first driver, if he reports the threshold truthfully throughout the game, then the best response of driver 2 will have no effect on the first driver's total reward $R_1 = \lfloor B/T^* \rfloor T^*$. Otherwise, for the first round n where he reports a higher threshold $T_{1,n}$, if $n \neq 1$, then the algorithm will use his previous reported threshold T^* as his reward, which does not affect the outcome of the game. But if $n = 1$, driver 2 can best response by reporting a threshold $T^* \leq T_{2,1} < T_{1,1}$, obtaining the reward in this round. Therefore, the total reward of driver 1 is upper bounded by the reward gained adopting the honest strategy $\lfloor B/T^* \rfloor T^*$. Therefore, we have

$$U_1(s) = BU_1 = \lfloor B/T^* \rfloor T^*$$

For the second driver and any strategy s_2, the first driver can best response by choosing the same strategy $s_1 = s_2$, since the algorithm is biased towards him in this scenario. As $B \leq NT^*$, we know that

$$U_2(s) = BU_2 = 0$$

Since for any i, we have $U_i(s) \geq BU_i$, the honest strategy s is a PCE when $B \leq NT^*$.

Case 2. $B \geq CNT^* = 2NT^*$

It is obvious that for any driver i, his total reward is maximized when he reports a threshold of B/CT^* in each round, and collecting $R_i = B/C$. If he ever attempts to report a higher threshold, the best response of the other player will make him strictly lose in this round, and thus in the whole game. Adopting the honest strategy s where each driver report B/CT^*, we have

$$U_i(s) = BU_i = B/C$$

for any i. Hence, s is a PCE when $B \geq CNT^* = 2NT^*$.

Case 3. $NT^* < B < 2NT^*$

This is the scenario where the budget is enough to actuate driver 1 in every round, but driver 2 only in some rounds. We first prove the following theorem:

Theorem 5.1. *For a fixed B, N and $C = 2$, there exists $n^* \in \{1, 2, 3, \ldots, N, N+1\}$, such that $\forall n < n^*$, only one car is selected to actuate, and $\forall n \geq n^*$, two cars are actuated.*

Proof. If this theorem does not hold, then there must exists a $n' \in \{1, 2, \ldots, N\}$, where two cars are actuated in round n', but only one car is actuated in $n'+1$. Because in each round n we select $K = \frac{B - B_{used}}{N-n+1}$ to actuate, if we denote $B - B_{used}$ in round n' as B_l, and the pay R estimated from both cars' threshold in round n' and $n'+1$ as R_1, R_2, this situation can be written as

$$\frac{B_l}{N - n' + 1} \geq 2R_1$$
$$\frac{B_l - 2T^*}{N - (n'+1) + 1} < R_2$$
$$R_1 \geq 2R_2$$

Expand two inequalities we have

$$B \geq (2N - 2n' + 2)R_1$$
$$B < (2N - 2n' + 2)R_2$$
$$R_1 \geq R_2$$

a contradition. Therefore the theorem holds. □

We are now ready to show that the honest strategy s is a PCE. We already know that

$$U_1(s) = \min(N, \lfloor B/T^* \rfloor)T^* = NT^*$$
$$U_2(s) = \lfloor (B - NT^*)/T^* \rfloor T^*$$

it suffices to show that $U_1(s) \geq BU_1, U_2(s) \geq BU_2$.

For driver 1, if he sticks to the honest strategy $s_1 = s$, then $R_1 = NT^*$ no matter what threshold is reported by driver 2. If he otherwise chooses to report a higher threshold, denote n as the first round where he does so, if $n > 1$ then the outcome does not change. But if $n = 1$, i.e. he reports a threshold $T_{1,1} > T^*$ from the first round, claim that driver 2's best response is reporting $T_{2,1}$ where $T^* \leq T_{2,1} < T_{1,1}$ in the first round.

This is because if driver 2 reports such a $T_{2,1} < T_{1,1}$, he gains an extra round of reward $T_{2,1}$ immediately in the first round, with the budget left being $B - T_{2,1}$. But if $T_{2,1} \geq T_{1,1}$, not only does

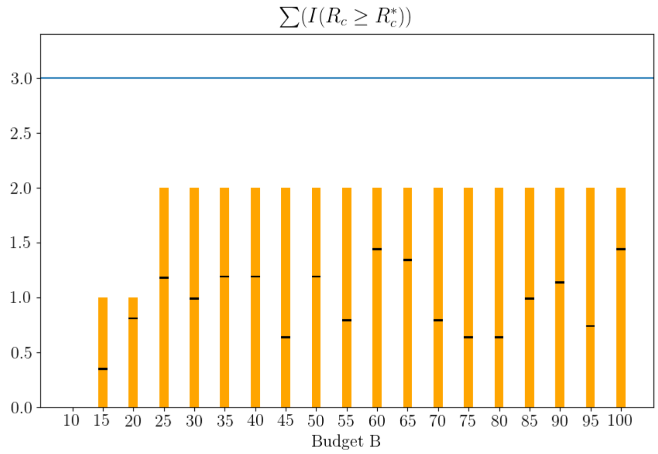

Figure 1: Simulation results based on different budget setup. x-axis is budget, y-axis is $\sum_{c=1}^{C} I(R_c \geq R_c^\star)$. $R_c^\star$ is the reward obtained from truthfully telling the threshold. R_c is the reward obtained from synthesized threshold telling strategy. The black line indicates the number of workers that gain a higher reward than R_c^*. (Note: synthesized threshold telling strategies do not include truthfully telling)

he collect zero reward in the first round, the remaining budget becomes $B - T_{1,1} < B - T_{2,1}$. Since subsequent rounds is only affected by the current round by the budget used and threshold reported, it is obvious that $\forall s_2 \in BR_2(s_1)$, where s_1 reports $T_{1,1}$, s_2 will report $T_{2,1} < T_{1,1}$. Then we know immediately that if driver 1 reports a higher threshold in the first round, his reward gained will be strictly less than NT^*. Hence, $BU_1 = NT^* \leq U_1(s)$.

For driver 2, no matter what threshold is reported by driver 2, driver 1's best response will be reporting the same threshold. According to theorem 5.1, since they are reporting the same threshold, player 2 can only collect reward in the last few rounds, if he ever collects at all. Then driver 2's maximal total reward can only be achieved when driver 1' pay in the previous rounds are minimized. Such a situation is achieved when driver 1 receives the minimal pay possible T^*. Therefore, $BU_2 = \lfloor (B - NT^*)/T^* \rfloor T^*$. Then we have

$$U_1(s) = NT^* = BU_1$$

$$U_2(s) = \lfloor \frac{B - NT^*}{T^*} \rfloor T^* = BU_2$$

Therefore, the honest strategy s is a PCE.

6 Simulation results

We ran a simulation of our policyt using the following setting: $N = 5, C = 3, T^* = 10$, and iterated over the budget from 10 to 100. Figure 1 shows the number of vehicles that gains higher by deviating from the optimal strategy will be always smaller than the total number of vehicles. This means that if someone deviates, there must be someone losing, which results in that the collaboration breaks.

7 Conclusion

In this report we purposed an algorithm to maximize the objective of the crowdsourcer, i.e. maximize the total number of task done by the worker, given that multiple workers could collaborate and exploit the reward policy. We observed that such a collaboration could fail when the reward mechanism is biased towards some known workers. Especially, for any two workers, the policy will favor one of them and make the pay even more biased to break the potential collaboration. We gave a formal proof of the optimality of the reward mechanism for the case of two workers, and also run a simulation to show that our algorithm indeed maximizes the objective of the crowdsourcer.

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