You Better Be Honest: Discouraging Free-Riding and False-Reporting in Mobile Crowdsourcing

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***Abstract*—Crowdsourcing is an emerging paradigm where users can pay for the services they need or receive rewards for providing services. One example in wireless networking is mobile crowdsourcing, which leverages a cloud computing platform for recruiting mobile users to collect data (such as photos, videos, mobile user activities, etc) for applications in various domains, such as environmental monitoring, social networking, healthcare, transportation, etc. However, a critical problem arises as how to ensure that users pay or receive what they deserve. Free-riding and false-reporting may make the system vulnerable to dishonest users. In this paper, we aim to design schemes to tackle these problems, so that each individual in the system is better off being honest. We first design a mechanism EFF which eliminates dishonest behavior with the help from a trusted third party for arbitration. We then design another mechanism DFF which, without the help from any third party, discourages free-riding and false-reporting. We prove that EFF eliminates the existence of free-riding and false-reporting, while guaranteeing truthfulness, individual rationality, budget-balance, and computational efficiency. We also prove that DFF is semi-truthful, which discourages dishonest behavior such as free-riding and false-reporting when the rest of the individuals are honest, while guaranteeing budget-balance and computational efficiency. Performance evaluation shows that within our mechanisms, no dishonest behavior could bring extra benefit for each individual.**

1. Introduction

A. Mobile Crowdsourcing

For the past few years, we have witnessed the proliferation of crowdsourcing [12] as it becomes a huge online market for labor and resource redistribution. which leverages a cloud computing platform for recruiting mobile users to collect data (such as photos, videos, mobile user activities, etc) for applications in various domains such as environmental monitoring, social networking, healthcare, transportation, etc. Several commercial websites, such as Yelp [1], Yahoo! Answers [2], Amazon Mechanical Turk [3], and UBER [4] provide trading markets where users can pay for the services they need (requesters) or receive rewards for providing services (service providers). An important functionality of these websites is to provide platforms not only to offer markets for labor and resource redistribution, but also to help deciding fair prices for all service providers and requesters.

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In most cases, a requester would post a task on one of these platforms, and wait till some service provider from the crowd to solve it. To incentivize service providers for their services, the requester needs to offer a certain amount of money. Service providers will get reward for finishing the tasks.

B. Auction Theory

Auction is an efficient mechanism for trading markets, with its advantage in discovering prices for buyers and sellers. Auctions involving the interactions among multiple buyers and multiple sellers are called *double auctions*. When determining payments for buyers and sellers, it is always feared that the prices are manipulated to make the free market vulnerable to dishonest individuals. Therefore, several economic properties, such as truthfulness, individual rationality, budget-balance, and computational efficiency are desired. Here are the definitions of these properties:

- Truthfulness: An auction is truthful if for any buyer or seller, no higher utility could be achieved by reporting a value deviating from its true valuation (or cost) regardless of the bids (or asks) from other individuals.
- Individual Rationality: An auction is individually rational if for any buyer or seller, it will not get a negative utility by revealing its true valuation (or cost).
- Budget-balance: An auction is budget-balanced if the auctioneer always makes a non-negative profit.
- Computational Efficiency: An auction is computationally efficient if the whole auction process can be conducted within polynomial time.

C. Free-riding and False-reporting in Crowdsourcing

Truthfulness of an auction can prevent individuals benefit from lying on the prices. However, this alone is not adequate. Free-riding and false-reporting, which are closely related to when the payment is made and when providers receive their money, can make the mechanism vulnerable to dishonest service providers and requesters.

If the payment is made *before* the task is done, a service provider always has the incentive to take the payment and devote no efforts to solve the task, which is known as "free-riding" [25]. If the payment is paid *after* the task is done, the requester always has the incentive to refuse the payment by lying about the outcome of this task, which is known as "false-reporting" [25]. Thus, extra precautions are necessary. Most current works [8, 11, 25] are focused on avoiding free-riding and false-reporting by building up reputation systems

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or grading systems. These mechanisms may discourage such dishonest behavior overall, but *based on the assumption that all individuals are patient and they would stay in the system*. However, in reality, some dishonest individuals may only stay in the system for a short period of time, and get huge rewards for being dishonest. In addition, many impatient users may leave the platform and switch to other websites since they feel unsafe and being cheated.

D. Game Theory

Game theory [19] is a field of study where interactions among different players are involved. Each player wants to maximize its own utility, which depends on not only its own strategies, but also other players' strategies. We need the concept of dominant strategy and Nash Equilibrium [14] as follows.

- Dominant Strategy: A strategy s (strongly) dominates all other strategies if the payoff to s is (strictly) no less than the payoff to any other strategy, regardless of the strategies chosen by other players.
- Nash Equilibrium (NE): When each player has chosen a strategy and no player can benefit by unilaterally changing its own strategy, then the current set of strategies and the corresponding payoffs constitute a Nash Equilibrium.

E. Summary of Contributions

In this paper, we design novel auction-based mechanisms to avoid free-riding and false-reporting. We use *any* existing truthful double auction scheme for winner selection and price determination. Each winner will submit a certain amount of money as a *warranty* for honest behavior. If the platform concludes it is not lying, the warranty will be returned. Otherwise, the warranty will be confiscated. Based on the reports from service providers and requesters, a final price will be determined by our mechanisms.

The main contributions of this paper are the following:

- To the best of our knowledge, we are the first to solve free-riding and false-reporting *in each single round*.
- We propose a mechanism **EFF**, which, with the help from a trusted third party for arbitration, eliminates the existence of free-riding and false-reporting, while guaranteeing truthfulness, individual rationality, budget-balance, and computational efficiency.
- We propose a mechanism **DFF**, which, without arbitration from any third party, discourages individuals from lying. We prove that **DFF** is semi-truthful, which means no individual could have a higher utility by lying when others are honest. We also prove that **DFF** is budget-balanced and computationally efficient.

The remainder of this paper is organized as follows. We briefly review some current literature on crowdsourcing mechanisms, truthful auctions and mechanisms avoiding free-riding and false-reporting in Section 2. In Section 3, we describe the system model. We present and analyze **EFF** and **DFF** in Section 4 and Section 5 respectively. We present performance evaluation in Section 6 and draw our conclusion in Section 7.

2. Related Work

In this section, we review some state-of-art research on crowdsourcing models, truthful auction mechanisms, and schemes tackling free-riding and false-reporting.

Many incentive mechanisms have been proposed for crowdsourcing and mobile sensing [7, 13, 16, 20]. In 2012, Yang *et al.* [24] proposed two models: user-centric and platform-centric models. In user-centric model, an auction-based mechanism is presented, which is computationally efficient, individually rational, profitable, and truthful. In platform-centric model, a Stackelberg game is formulated and a unique Stackelberg equilibrium is calculated to maximize the platform utility.

Many other truthful auctions also fit for crowdsourcing and mobile sensing. There are two basic truthful double auctions, VCG [5, 10, 21] and McAfee [17], from which most of the current truthful auctions are derived. Along this line, many mechanisms [6, 9, 15, 18, 22, 23] are proposed. While most of these are not specifically designed for crowdsourcing platforms, with minor modifications, they can be applied into the scenario.

These auction schemes are based on an assumption that all service providers will successfully finish the assigned tasks, and all requesters are satisfied with tasks' accomplishment status. This may not always happen. Therefore, there are works focusing on how to make the mechanism robust against free-riding and false-reporting [8, 11, 25]. In these papers, free-riding and false-reporting are avoided by building reputation systems or grading systems. Such systems are based on the assumption that *all individuals are patient and will stay in the system for a very long time*. Thus, if there is an individual who stays only for a short period of time, it may gain extra benefits by free-riding or false-reporting. Impatient users may feel being cheated and turn to other platforms.

3. System Model

There is a set of m *requesters* $\mathcal{R} = \{R_1, R_2, ..., R_m\}$. For each R_i, it requires services to finish its own task T_i with a private *valuation* v_i. Each T_i is tagged with a *bid* b_i by R_i, which is the maximum amount R_i is willing to pay in the auction, and b_i is not necessarily equal to v_i. We define the vector $\mathbf{b} = (b_1, b_2, ..., b_m)$.

There is a set of n service *providers* $\mathcal{P} = \{P_1, P_2, ..., P_n\}$. Each provider P_j has a *cost* $c_j^i > 0$ to finish T_i, and c_j^i is set to be $+\infty$ if P_j is unable to finish T_i. P_j would post an *ask* a_j^i for T_i, which is the minimum amount P_j demands if P_j finishes T_i, and a_j^i is not necessarily equal to c_j^i. We define the vector $\mathbf{a}_j = (a_j^1, a_j^2, ..., a_j^m)$ and the matrix $\mathbb{A} = (\mathbf{a}_1, \mathbf{a}_2, ..., \mathbf{a}_n)$.

We assume that service providers and requesters are non-colluding. By applying a sealed-bid and single-round double auction, we will have a *winning buyer-seller assignment* $\delta(\cdot)$, such that each winning provider P_j is assigned to finish $T_{\delta(j)}$. Each provider is assigned to at most one task at the same time, and $\delta(j) = 0$ if P_j is not assigned to any tasks. R_i will be *charged* β_i, and P_j will *receive* $\alpha_j^{\delta(j)}$. We define $\beta = (\beta_1, \beta_2, ..., \beta_m)$, $\alpha_i = (\alpha_i^1, \alpha_i^2, ..., \alpha_i^m)$, and $\alpha = (\alpha_1, \alpha_2, ..., \alpha_n)$. The platform (auctioneer) has a profit

TABLE 1
UTILITIES OF R_i AND P_j IN **EFF**

R_i \ P_j	(F,F)	(F,N)	(N,F)	(N,N)
(F,F)	$(v_i-\beta_i, \alpha_j^i - c_j^i)$	$(v_i-\beta_i, \alpha_j^i - c_j^i - \tau_i)$		
(F,N)	$(v_i-\beta_i-\tau_i, \alpha_j^i - c_j^i)$	$(v_i, -c_j^i)$		
(N,F)			$(-\beta_i, \alpha_j^i)$	$(-\tau_i, 0)$
(N,N)			$(0, -\tau_i)$	$(0,0)$

$\Sigma_{(R_i,P_j)\in\mathcal{W}}(\beta_i - \alpha_j^i)$ from the auction, where $\mathcal{W}$ is the set of winning requester-provider pairs. In the rest of the paper, we will use the terminologies of buyer and requester, seller and provider, and auctioneer and platform interchangeably.

The *auction mechanism*, denoted as $\mathbb{M}$, should take the set of requesters $\mathcal{R}$, the set of providers $\mathcal{P}$, bid vector $\mathbf{b}$, and ask matrix $\mathbb{A}$ as input. $\mathbb{M}$ should output the winning assignment $\delta(\cdot)$ and the winning payments α and β. Therefore, we have $(\delta(\cdot),\alpha,\beta) \leftarrow \mathbb{M}(\mathcal{R},\mathcal{P},\mathbf{b},\mathbb{A})$. During this process, $\mathbb{M}$ needs to maintain several economic properties: truthfulness, individual rationality, budget-balance, and computational efficiency. As discussed in Section 2, there are many auction models satisfying our requirements. TASC [23] is one such auction, and is used in our implementations.

For each $(R_i, P_j) \in \mathcal{W}$, both R_i and P_j report to the platform on whether T_i has been successfully finished. R_i and P_j both know the true accomplishment status of T_i (*the ground truth*). However, the platform is not aware of the ground truth. Each individual will either report F to the platform, which is short for Finished, or N, which is short for Not finished. The platform decides the final payment for each individual. If both R_i and P_j submit the same report, the platform would believe both of them are telling the truth. Otherwise, the platform would conclude that at least one of them is lying and consult for arbitration if available. We assume that between R_i and P_j, there are no ambiguities on T_i's accomplishment status.

We define the *utility of* R_i as

$$U_i^R = x_i v_i - (\beta_i + w_i^R - b_i'), \tag{3.1}$$

where x_i is the indicator of T_i. If T_i is successfully finished, $x_i = 1$; and $x_i = 0$ otherwise. w_i^R is the warranty R_i pays to the platform, and b_i' is the amount of money R_i receives after it has already submitted $\beta_i + w_i$ to the platform. The *utility for* P_j is

$$U_j^P = ({a'}_j^{\delta(j)} - w_j^P) - y_j^{\delta(j)} c_j^{\delta(j)}, \tag{3.2}$$

where $y_j^{\delta(j)}$ is the indicator of P_j's true devotion on $T_{\delta(j)}$. If P_j has worked on $T_{\delta(j)}$, $y_j^{\delta(j)} = 1$; and $y_j^{\delta(j)} = 0$ otherwise. w_j^P is the warranty from P_j, and ${a'}_j^{\delta(j)}$ is the final amount P_j receives after it has already submitted w_j^P to the platform. The *platform utility* is

$$U = \sum\nolimits_{(R_i,P_j)\in\mathcal{W}} (\beta_i + w_i^R - b_i') - ({a'}_j^{\delta(j)} - w_j^P) - z_i\tau_i, \tag{3.3}$$

where z_i is the indicator of arbitration on T_i, and τ_i is the corresponding arbitration fee. If the platform has consulted for arbitration on T_i, $z_i = 1$; and $z_i = 0$ otherwise.

4. EFF: ELIMINATING FREE-RIDING AND FALSE-REPORTING WITH ARBITRATION

In this section, we present an auction-based crowdsourcing mechanism **EFF**, which, with the help from a trusted third party for arbitration, eliminates free-riding and false-reporting.

A. Description of EFF

In **EFF**, a trust-worthy third party is available when necessary, who provides arbitration on T_i's accomplishment status with an arbitration fee $\tau_i > 0$. T_i is a value known by all service providers, requesters, and the platform.

The first part of **EFF** is auction $\mathbb{M}$, where the winning requester-provider set $\mathcal{W}$ is decided, along with truthful payments α and β. For each $(R_i, P_j) \in \mathcal{W}$, R_i pays $\beta_i + \tau_i$ to the platform, and P_j pays τ_i to the platform. In the rest of the paper, unless specified, we assume $(R_i, P_j) \in \mathcal{W}$. The warranties for R_i and P_j are $w_i^R = \tau_i$ and $w_j^P = \tau_i$ respectively.

Both R_i and P_j will submit their reports on T_i's accomplishment status. Since the ground truth could not be detected by the platform, the platform would consult the third party for arbitration when necessary. After the arbitration result comes out, the honest user gets the warranty back, and the dishonest user cannot.

Based on the reports from R_i and P_j, the platform will decide final payments according to the following strategies.

- If both R_i and P_j submit the same status, the platform would believe that they are revealing the truth.
- If R_i and P_j submit different reports, the platform would consult for arbitration. The platform will pay τ_i to the third party as arbitration fee.
- If T_i has been successfully finished, α_j^i will be paid to P_j. Otherwise, β_i will be returned to R_i.

We form a game between R_i and P_j. The strategies are submitting F or N and the utilities are shown in Table 1.

For the 2-tuples in the first row and the first column, the first elements stand for the ground truth on T_i, and the second elements stand for the submitted reports. For the rest of the 2-tuples, the first elements are utilities for R_i, and the second elements are utilities for P_j. Note that there are eight blank cells, as there is only one ground truth on T_i at the same time.

According to Table 1, *there is a unique NE for each ground truth. When the ground truth is* F*, and both* R_i *and* P_j *submit* F*, an NE is reached. When the ground truth is* N*, and both* R_i *and* P_j *submit* N*, another NE is reached. There are no other NEs in this game.*

B. Analysis of EFF

In this subsection, we prove several properties of **EFF**.

Theorem 1: EFF eliminates free-riding and false-reporting, while guaranteeing truthfulness, individual rationality, budget-balance, and computational efficiency.

To prove this theorem, we need the following four lemmas.

Lemma 4.1: Neither the service provider nor the requester could have a positive increment in utility by being dishonest.

Proof: There are two ways for R_i and P_j acting dishonestly: the first is bidding other than their true valuations or costs in the auction, and the second is submitting false reports. Since $\mathbb{M}$ is budget-balanced and individually rational, $b_i \geq \beta_i \geq \alpha_j^i \geq a_j^i > 0$.

Suppose R_i loses the auction by bidding $b_i = v_i$. Its original utility is 0. To win the auction, it has to make a higher bid, and the winning payment is no less than b_i by the truthfulness of $\mathbb{M}$. Based on Table 1, its utility is no more than $v_i - b_i = 0$.

Suppose P_j loses the auction by asking $a_j^i = c_j^i$. Its original utility is 0. To win the auction, it has to lower its ask, and the new winning price is no more than a_j^i. Based on Table 1, its utility is no more than $a_j^i - c_j^i = 0$.

For $(R_i, P_j) \in \mathcal{W}$, suppose P_j successfully finishes T_i. Since the auction is truthful, P_j will not receive a higher payment by asking other than c_j^i, and R_i will not pay a lower price by bidding other than v_i. P_j will report F since it is P_j's strongly dominant strategy according to Table 1. Therefore, R_i will report F as P_j will always report F. Thus, R_i could not get a higher utility by asking a different value or submitting a false report, and neither could P_j.

Now we suppose that P_j fails to finish T_i. R_i will report N as it is R_i's strongly dominant strategy, and P_j will report N as R_i will always report N. Thus, neither R_i nor P_j could get a utility gain by bidding other than its true valuation, or submitting a false report.

To sum up all cases, no individual could improve its own utility by being dishonest. ∎

If P_j finishes T_i, its utility is $\alpha_j^i - c_j^i \geq 0$. If P_j does not finish T_i, its utility is $-y_j^i c_j^i \leq 0$. Thus, P_j prefers finishing the task to free-riding. It is the same reason that false-reporting is eliminated in **EFF**.

Lemma 4.2: EFF is individually rational.

Proof: Since $\mathbb{M}$ is individually rational, $v_i - \beta_i \geq 0$ and $\alpha_j^i - c_j^i \geq 0$. From Table 1, as long as R_i (P_j) is honest, R_i (P_j) will not receive a negative utility. ∎

Lemma 4.3: EFF is budget-balanced.

Proof: If the ground truth is F, or both R_i and P_j submit F, the platform utility on (R_i, P_j) is $U(R_i, P_j) = \beta_i - \alpha_j^i \geq 0$ as $\mathbb{M}$ is budget-balanced. If the ground truth is N, or both R_i and P_j submit N, $U(R_i, P_j) = 0$. Thus, $\Sigma_{(R_i,P_j)\in\mathcal{W}} U(R_i, P_j) \geq 0$. ∎

Lemma 4.4: EFF is computationally efficient.

Proof: Since $\mathbb{M}$ is computationally efficient, and report-submitting, arbitration, and pricing take constant time, **EFF** is computationally efficient. ∎

Lemmas $4.1 - 4.4$ complete the proof for Theorem 1.

5. DFF: Discouraging Free-riding and False-reporting without Arbitration

In **EFF**, with the help from a trusted third party, the platform can consult for arbitration when it is difficult to decide which individual is not revealing the ground truth. Therefore, free-riding and false-reporting could not benefit any service provider or requester in **EFF**.

However, in reality, it is not always true that the platform is able to find such a trustworthy third party for arbitration. In this section, we present another mechanism **DFF**, which, without the help from any other third party for arbitration, discourages free-riding and false-reporting, while guaranteeing desired economic properties.

A. Description of DFF

Same as **EFF**, the first part of **DFF** is the auction $\mathbb{M}$. We define a constant system parameter $\theta \geq \frac{1}{2}$. By the end of the auction $\mathbb{M}$, each winning requester R_i pays $\beta_i + \theta\beta_i$ to the platform, where β_i is the truthful payment decided by $\mathbb{M}$, and $w_i^R = \theta\beta_i$ is R_i's warranty. For each winning service provider P_j, if it is assigned to finish T_i, P_j will pay $w_j^P = \theta\alpha_j^i$ as its warranty.

After $\mathbb{M}$, both R_i and P_j submit their reports on T_i to the platform. Based on these reports, the platform decides the final payments according to the following table:

TABLE 2
FINAL PAYMENTS OF R_i AND P_j IN **DFF**

R_i \ P_j	Finished	Not Finished
Finished	$(\theta\beta_i, (1+\theta)\alpha_j^i)$	(β_i, α_j^i)
Not Finished	$(0, 0)$	$((1+\theta)\beta_i, \theta\alpha_j^i)$

Each cell in Table 2 contains a 2-tuple, $(b'_i, {a'}_j^i)$, where b'_i is the payment R_i receives after it has already submitted $(1+\theta)\beta_i$ to the platform, and ${a'}_j^i$ is the payment P_j receives after it has already submitted $\theta\alpha_j^i$ to the platform.

Based on Table 2, utilities are derived in Table 3. Notations in Table 3 stand for the same meanings as those in Table 1.

According to Table 3, there are two NEs for each ground truth, which are when both R_i and P_j submit F and when both R_i and P_j submit N.

B. Analysis of DFF

In this subsection, we prove several properties of **DFF**.

Definition 5.1: A mechanism is *semi-truthful* if each individual has no positive increment in utility when it unilaterally behaves dishonestly while others are being honest.

Theorem 2: DFF is semi-truthful, budget-balanced, and computationally efficient.

To prove Theorem 2, we need the following three lemmas:

Lemma 5.1: DFF is semi-truthful.

Proof: Suppose R_i loses the auction by bidding $b_i = v_i$. Its original utility is 0. To win the auction, it has to make a higher bid and the winning price will be no lower than b_j due to the truthfulness of $\mathbb{M}$. According to Table 2, its utility is no more than $v_j - b_j = 0$.

TABLE 3
UTILITIES OF R_i AND P_j IN **DFF**

R_i \ P_j	(F, F)	(F, N)	(N, F)	(N, N)
(F, F)	$(v_i - \beta_i, \alpha_j^i - c_j^i)$	$(v_i - \theta\beta_i, (1-\theta)\alpha_j^i - c_j^i)$		
(F, N)	$(v_i - (1+\theta)\beta_i, -\theta\alpha_j^i - c_j^i)$	$(v_i, -c_j^i)$		
(N, F)			$(-\beta_i, \alpha_j^i)$	$(-\theta\beta_i, (1-\theta)\alpha_j^i)$
(N, N)			$(-(1+\theta)\beta_i, -\theta\alpha_j^i)$	$(0, 0)$

Similarly, we consider a service provider P_j who fails to win the auction by asking $a_j^i = c_j^i$. Its original utility is 0. To win the auction, it has to lower its ask and the winning price will be no more than a_i^j, as $\mathbb{M}$ is truthful. Based on Table 2, its utility is no more than $a_j^i - c_j^i = 0$

For $(R_i, P_j) \in \mathcal{W}$, consider the case that P_j successfully finishes T_i. If no agent lies throughout the process, R_i's utility is $v_i - \beta_i \geq 0$, and P_j's utility is $\alpha_j^i - c_j^i \geq 0$. Suppose R_i lies about its bid, it will not pay a lower payment, due to the truthfulness of $\mathbb{M}$. If R_i lies by reporting N instead of F, and P_j does not lie and reports F, R_i's utility is $v_i - (1+\theta)\beta_i' \leq v_i - (1+\theta)\beta_i \leq v_i - \beta_i$, where β_i' is the new payment after R_i changes its bid. Thus, R_i has no incentive to lie. Symmetrically for P_j, by lying about its ask, it will not receive a higher payment. If P_j lies by reporting N, and R_i does not lie and reports F, P_j's new utility is $(1-\theta){\alpha'}_j^i - c_j^i < \alpha_j^i - c_j^i$. Thus, P_j has no incentive to lie.

Suppose P_j fails to finish T_i. When no agent lies, both R_i's and P_j's utilities are 0. When R_i submits F dishonestly, and P_j reports N honestly, R_i's utility is $-\theta\beta_i' \leq -\theta\beta_i \leq 0$, where β_i' is the new payment after R_i changes its bid. Therefore, R_i has no incentive to be dishonest. Similarly, suppose P_j unilaterally lies about the accomplishment status, the new utility of P_j is $-\theta\alpha_j^i \leq -\theta{\alpha'}_j^i \leq 0$, where ${\alpha'}_j^i$ is the new payment after P_j changes its ask. Therefore, P_j has no incentive to lie as well.

To sum up all cases, no individual could improve its utility by unilaterally being dishonest. ■

Lemma 5.2: **DFF** guarantees budget-balance.

Proof: For $(R_i, P_j) \in \mathcal{W}$, there are four possible payments according to Table 2. Since $\mathbb{M}$ is individually rational and budget-balanced, we have $b_i \geq \beta_i \geq \alpha_j^i \geq a_j^i$. If both R_i and P_j submit F, the utility of the platform on this winning pair is $U(R_i, P_j) = \beta_i - \alpha_j^i \geq 0$. If R_i submits N and P_j submits F, we have $U(R_i, P_j) = (1+\theta)\beta_i + \theta\alpha_j^i \geq 0$. If R_i submits F and P_j submit N, $U(R_i, P_j) = ((1+\theta)\beta_i - \beta_i) - (\alpha_j^i - \theta\alpha_j^i) \geq (1-\theta)(\beta_i - \alpha_j^i) \geq 0$. If both of them submit N, $U(R_i, P_j) = 0$. Thus, $\Sigma_{(R_i, P_j) \in \mathcal{W}} U(R_i, P_j) \geq 0$. ■

Lemma 5.3: **DFF** is computationally efficient.

The proof is the same as Lemma 4.4 since the two mechanisms have the same time complexity.

Lemmas 5.1 – 5.3 complete the proof for Theorem 2.

However, full truthfulness could not be satisfied within **DFF**. The two NEs indicate that revealing the truth is not always the dominant strategy for each individual. Another important economic property **DFF** could not satisfy is individual rationality. Because when T_i is not successfully finished, and P_j lies about the status, R_i's utility is negative if R_i reports honestly.

6. PERFORMANCE EVALUATION

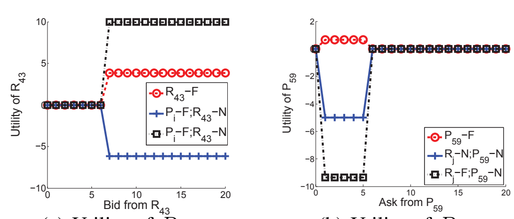
To evaluate the performance of the mechanisms presented in this paper, we implemented both **EFF** and **DFF**, and carried out extensive testing on various cases.

In both **EFF** and **DFF**, we used TASC [23] as the auction model $\mathbb{M}$. For **EFF**, we set $\tau_i = 10$ for all T_i. For **DFF**, we set $\theta = 0.7$. Note that this setting is for simplicity only. For properties of τ_i and θ, see Section 4 and Section 5 respectively. All bids and asks are uniformly and randomly distributed over $[0, 20]$.

To study the behavior of requesters and providers, we set $m = n = 100$, and ran both **EFF** and **DFF**. The corresponding results are reported in Figs. 1-4, where R_{43} is a randomly picked requester and P_{59} is a randomly picked provider, with $v_{43} = 10$ and $c_{59}^{43} = 5$.

To study the behavior of the platform utility as a function of number of users, we first fixed $m = 100$ and let n increase from 10 to 1000; then fixed $n = 100$ and let m increase from 10 to 1000. When applying TASC, we used two different matching algorithms: Random Matching (RAND) and Maximum Matching (MM) [23]. The corresponding results are reported in Fig. 5. These results are averaged over 100 runs for each case. We did not report running time, since it is dominated by the running time of $\mathbb{M}$.

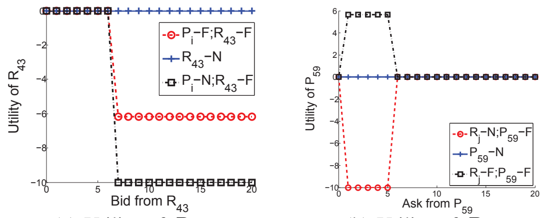
First we monitor the utilities of R_{43} and P_{59} in **EFF**. Fig. 1 shows the utilities of R_{43} and P_{59} respectively, when the service provider successfully finishes the task in **EFF**. From Fig. 1a, we observe that R_{43} cannot have a utility higher than the utility it has when bidding $b_{43} = v_{43} = 10$. Similarly, from Fig. 1b, we observe that P_{59} cannot have a utility higher than the utility it has when asking $a_{59}^{43} = c_{59}^{43} = 5$. From Fig. 1b, we observe that reporting F is P_{59}'s dominant strategy. Thus, R_{43} will report F. Therefore, no individual could get a positive utility increment by being dishonest.



(a) Utility of R_{43} (b) Utility of P_{59}

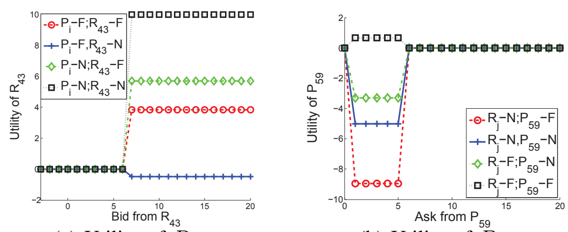
Fig. 1. Finished tasks with arbitration

Fig. 2 shows the utilities when service providers did not finish their tasks in **EFF**. Again, we observe that no individual can get a positive utility increment by being dishonest using a similar approach as stated above.



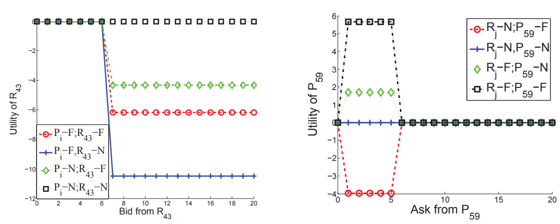
(a) Utility of R_{43} (b) Utility of P_{59}
Fig. 2. Unfinished tasks with arbitration

Next we monitor the utilities of R_{43} and P_{59} in **DFF**. From Fig. 3, we observe that when the service provider finishes the task, it is always better that both the service provider and corresponding requester submit the same report. Therefore, there is no incentive for an individual to be dishonest when the other is honest.



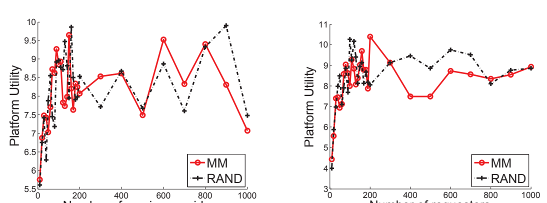
(a) Utility of R_{43} (b) Utility of P_{59}
Fig. 3. Finished tasks without arbitration

Fig. 4 shows the semi-truthfulness when the service provider fails to finish the task in **DFF**. Again, we observe that there is no incentive for an individual to be dishonest when the other is honest.



(a) Utility of R_{43} (b) Utility of P_{59}
Fig. 4. Unfinished tasks without arbitration

Next we focus on the platform utility. From Fig. 5, we observe that the platform will not have a negative utility, and the platform utility is not monotonically increasing. This is because the platform utility depends on not only the number of winning pairs, which is bounded by $\min\{m,n\}$, but also the final prices. Therefore, when $\min\{m,n\}$ increases, the platform utility increases. When the number of winning pairs reaches $\min\{m,n\}$, the final payment decides the platform utility.



(a) Platform utility, $m = 100$ (b) Platform utility, $n = 100$
Fig. 5. Platform utilities under **EFF**

7. CONCLUSION

In this paper, we proposed two novel mechanisms to tackle free-riding and false-reporting. We first presented **EFF** and proved that with the help from a trusted third party for arbitration, **EFF** can eliminate free-riding and false-reporting, while guaranteeing truthfulness, individual rationality, budget-balance, and computational efficiency. We also presented **DFF** and proved that without arbitration, **DFF** discourages dishonest behavior, while guaranteeing semi-truthfulness, budget-balance, and computational efficiency. We implemented **EFF** and **DFF**, and further numerical results support our theoretical analysis.

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