

Keep Your Promise: Mechanism Design Against Free-Riding and False-Reporting in Crowdsourcing

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Abstract—Crowdsourcing is an emerging paradigm where users can have their tasks completed by paying fees, or receive rewards for providing service. A critical problem that arises in current crowdsourcing mechanisms is 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 design schemes to tackle these problems, so that each individual in the system is better off being honest and each provider prefers completing the assigned task. 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 dishonest behavior. 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 transaction-wise budget-balance and computational efficiency. Performance evaluation shows that within our mechanisms, no user could have a utility gain by unilaterally being dishonest.

Index Terms—Crowdsourcing, false-reporting, free-riding, game theory, incentive mechanisms.

I. INTRODUCTION

A. Crowdsourcing

FOR THE past few years, we have witnessed the proliferation of crowdsourcing [16] as it becomes a booming online market for labor and resource redistribution. One example is mobile crowdsourcing [25], [34], which leverages a cloud computing platform for recruiting mobile users to collect data (such as photos, videos, and mobile user activities) for applications in various domains such as environmental monitoring, social networking, healthcare, and transportation. Several

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commercial crowdsourcing websites, such as Yelp [1], Yahoo! Answers [2], Amazon Mechanical Turk [3], and UBER [4], provide trading markets where some users (*service requesters*) can have their tasks completed by paying fees, and some other users (*service providers*) can receive rewards for providing service. An important functionality of these websites is to empower platforms not only to offer markets for laboring and resource redistribution, but also to help decide fair prices for all providers and requesters.

In general, a requester would post a task on one of these platforms, and wait till some provider to work on it. To incentivize providers for their service, the requester needs to offer a certain reward. A provider will get reward as compensation for its cost of completing the task.

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* [12]. 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.

- 1) **Truthfulness:** An auction is truthful if no individual can achieve a higher utility by reporting a value deviating from its true valuation (or cost) regardless of the bids (or asks) from other individuals.
- 2) **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).
- 3) **Budget-balance:** An auction is budget-balanced if the auctioneer always makes a nonnegative profit.
- 4) **Computational efficiency:** An auction is computationally efficient if the whole auction process can be conducted within polynomial time.

Among these properties, truthfulness is the crowning jewel that incentivizes all participants to be honest during the auction [5], [11], [19], [27], [34], [37]. However, this alone cannot guarantee the robustness of the mechanism, since other dishonest behavior, such as free-riding and false-reporting (to be defined later), may make the crowdsourcing system vulnerable.

C. Free-Riding and False-Reporting in Crowdsourcing

Truthfulness of an auction can prevent individuals benefit from lying about the prices. However, this alone is not adequate. Free-riding and false-reporting can make the mechanism vulnerable to dishonest users.

If the payment is made *before* the provider starts to work, a provider always has the incentive to take the payment and devote no effort to complete the task, which is known as *free-riding* [36]. If the payment is made *after* the provider completes its work, the requester always has the incentive to refuse the payment by lying about the status of this task, which is known as *false-reporting* [36]. Thus, extra precautions are necessary. Most recent works [10], [15], [36] are focused on avoiding free-riding and false-reporting by building up reputation systems 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 stay in the system for a short period of time, and get huge rewards by being dishonest. In addition, impatient users may leave the platform since they feel unsafe and being cheated.

In this paper, we tackle free-riding and false-reporting by a game-theoretic approach, such that free-riding and false-reporting are eliminated or discouraged.

D. Game Theory Basics

Game theory [23] 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* (NE) [24] as follows.

- 1) *Dominant strategy*: A strategy s dominates all other strategies if the payoff to s is no less than the payoff to any other strategy, regardless of the strategies chosen by other players. s is a *strongly dominant strategy* if its payoff is strictly larger than the payoff to any other strategy.
- 2) *Nash equilibrium*: When each player has chosen a strategy and no player can benefit by unilaterally changing its strategy, the current set of strategies constitutes an NE.

Extensive-form game theory [23] is an important branch of game theory. An extensive-form game is a game where sequencing players' strategies and their choices at each decision point is allowed. The corresponding equilibrium, which is called *subgame perfect equilibrium* (SPE), is a strategy profile where in every subgame, an NE is reached by the corresponding subset of strategies.

E. Summary of Contributions

In this paper, we design two novel auction-based mechanisms EFF and DFF, to avoid free-riding and false-reporting, while incentivizing providers to complete their assigned tasks. These mechanisms are based on *any* existing truthful double auction scheme for winner selection and pricing. Each auction winner is required to submit a *warranty* first, then submit a report on the status of the corresponding task. Based on these reports from providers and requesters, the final payments are determined by the platform.

The main contributions of this paper are the following.

- 1) To the best of our knowledge, we are the first to solve free-riding and false-reporting *in each single round*.
- 2) We design a mechanism EFF, which, with the help of arbitrations, eliminates free-riding and false-reporting, and incentivizes providers to complete their assigned tasks. We also prove that EFF is truthful, transaction-wise, budget-balanced, and computationally efficient.
- 3) We design a mechanism DFF, which, without any arbitration, discourages individuals from being dishonest. We prove that DFF is semi-truthful, which means that no individual could have a higher utility by lying when others are honest. We also prove that DFF is transaction-wise budget-balanced and computationally efficient, while incentivizing providers to finish their assigned tasks.

The remainder of this paper is organized as follows. In Section II, we briefly review the current literature on crowdsourcing mechanisms, truthful auctions, and mechanisms avoiding free-riding and false-reporting. In Section III, we describe the system model. We present and analyze EFF and DFF in Sections IV and V, respectively. We present performance evaluation in Section VI and draw our conclusion in Section VII.

II. RELATED WORK

Many incentive mechanisms have been proposed for crowdsourcing and mobile sensing [5], [6], [9], [11], [17], [20], [26], [27], [31], [32], [34], [37]. In 2012, Yang *et al.* [34] studied two models: 1) user-centric and 2) platform-centric models. For the user-centric model, an auction-based mechanism is presented, which is computationally efficient, individually rational, profitable, and truthful. For the platform-centric model, the Stackelberg game is formulated and the unique Stackelberg equilibrium is calculated to maximize the platform utility. In [9], DiPalantino and Vojnovic proposed an all-pay auction, where each provider may choose the job that it wants to work on. In [17], an online question and answer forum was introduced, where each user has a piece of information and can decide when to answer the question. Singla and Krause in [27] proposed BP-UCB, which is an online truthful auction mechanism achieving near-optimal utilities for all providers. A crowdsourcing Bayesian auction is proposed in [5], where the system is aware of the distribution of valuations of all users. With this assumption, two techniques were applied to the new Bayesian optimal auction with high system performance. Zhao *et al.* [37] proposed an online truthful auction for crowdsourcing with a constant approximation ratio with respect to the platform utility. In [11], a truthful auction algorithm of task allocation to optimize the total utility of all smartphone users was proposed by Feng *et al.* for the offline model, and an online model was also introduced which reaches a constant approximation ratio of $\frac{1}{2}$.

Many other truthful auctions also fit for crowdsourcing and mobile sensing. There are two basic truthful double auctions, VCG [7], [14], [28] and McAfee [21], from which most of the current truthful auctions are derived. Along this line, many mechanisms [8], [13], [18], [19], [22], [29], [33] are proposed. While they are not specifically designed for crowdsourcing

platforms, they can be applied to the scenario with minor modifications.

These auction schemes are based on the assumption that all providers will complete the assigned tasks, and all requesters are satisfied with the status of the tasks. This may not always happen. Therefore, there are works focusing on how to make the mechanism robust against free-riding and false-reporting [10], [15], [36]. 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, a user may gain extra benefit by free-riding or false-reporting during a short period of time. Impatient users may feel being cheated and turn to other platforms.

III. SYSTEM MODEL

In this section, we present the crowdsourcing model and the corresponding double auction model, and define the utilities for the platform, the providers, and the requesters.

There is a set of m requesters $\mathcal{R} = \{R_1, R_2, \dots, R_m\}$. For each R_i , it requires service to complete its task T_i , which has a private valuation $v_i > 0$ to R_i if T_i is completed. T_i is tagged with a bid b_i by R_i , which is the maximum reward that R_i is willing to pay for the completion of T_i . Note that b_i is not necessarily equal to v_i . We define the bid vector $\mathbf{b} = (b_1, b_2, \dots, b_m)$.

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

We assume that providers and requesters are noncolluding. By applying a sealed-bid single-round double auction where requesters are buyers and providers are sellers, we get a set \mathcal{W} of winning requester-provider pairs, such that $(R_i, P_j) \in \mathcal{W}$ if and only if P_j is assigned to complete T_i . Each provider is assigned to at most one task, while no more than one provider works on each task. We define the function $\delta(\cdot) : \mathcal{P} \rightarrow \mathcal{R}$ such that $\delta(j) = i$ if and only if $(R_i, P_j) \in \mathcal{W}$, and $\delta(j) = 0$ if P_j is not assigned to any task. As a result of the auction, R_i will be charged β_i , and P_j will receive $\alpha_j^{\delta(j)}$. As a technical convention, we define $\beta_i = 0$ if R_i is not a winning requester, and $\alpha_j^i = 0$ if $(R_i, P_j) \notin \mathcal{W}$. We define $\beta = (\beta_1, \beta_2, \dots, \beta_m)$, $\alpha_j = (\alpha_j^1, \alpha_j^2, \dots, \alpha_j^m)$, and $\alpha = (\alpha_1; \alpha_2; \dots; \alpha_n)$. The platform (auctioneer) has a profit $\sum_{(R_i, P_j) \in \mathcal{W}} (\beta_i - \alpha_j^i)$ from the auction.

The auction mechanism, denoted as \mathbb{M} , takes the bid vector \mathbf{b} and the ask matrix \mathbb{A} as input. \mathbb{M} outputs the winning requester-provider pair set \mathcal{W} and the payments α and β . Thus, we have $(\mathcal{W}, \beta, \alpha) \leftarrow \mathbb{M}(\mathbf{b}, \mathbb{A})$.

We call an auction mechanism \mathbb{M} transaction-wise budget-balanced if $\beta_i \geq \alpha_j^i$, for each $(R_i, P_j) \in \mathcal{W}$. Note that transaction-wise budget-balance implies budget-balance, i.e.,

$\sum_{(R_i, P_j) \in \mathcal{W}} (\beta_i - \alpha_j^i) \geq 0$. Throughout this paper, we assume that \mathbb{M} is truthful, individually rational, transaction-wise budget-balanced, and computationally efficient. All mechanisms in [8], [18], [29], [31], and [33] satisfy these properties. In particular, Truthful Auction Scheme for Cooperative communications (TASC) [33] is used in our implementation.

For each $(R_i, P_j) \in \mathcal{W}$, the platform collects warranties from both R_i and P_j . We model the postauction process as an extensive-form game between P_j and R_i . In this game, P_j first decides the effort toward completing T_i ; then, R_i and P_j evaluate the result and submit independent reports on the status of T_i to the platform. We assume that P_j is capable of completing T_i ; hence, the status of T_i depends on the willingness of P_j . The reports are either **C**, which is short for *Completed*, or **I**, which is short for *Incomplete*. Both R_i and P_j know the status of T_i . However, the platform is not aware of T_i 's status. The platform decides the final payment for each individual according to these reports. If R_i and P_j submit the same report, the platform would believe that both of them are telling the truth. Otherwise, the platform concludes that one of them lies and consults for arbitration if available. We assume that there are no ambiguities on the status of T_i .

The utility of R_i is defined as

$$U_i^R = x_i v_i - (w_i^R - \bar{\beta}_i) \quad (1)$$

where x_i is the indicator of the status of T_i : $x_i = 1$ if T_i is completed; $x_i = 0$ otherwise. w_i^R is the warranty that R_i pays to the platform, and $\bar{\beta}_i$ is the final payment that R_i receives from the platform after the platform collects the reports.

The utility of P_j is defined as

$$U_j^P = (\bar{\alpha}_j^{\delta(j)} - w_j^P) - y_j^{\delta(j)} c_j^{\delta(j)} \quad (2)$$

where $y_j^{\delta(j)}$ is the indicator of P_j 's devotion on $T_{\delta(j)}$: $y_j^{\delta(j)} = 1$ if P_j worked on $T_{\delta(j)}$; $y_j^{\delta(j)} = 0$ otherwise. w_j^P is the warranty from P_j , and $\bar{\alpha}_j^{\delta(j)}$ is the final amount that P_j receives from the platform after the platform collects the reports.

The platform utility is defined as

$$U = \sum_{(R_i, P_j) \in \mathcal{W}} \left[(w_i^R - \bar{\beta}_i) + (w_j^P - \bar{\alpha}_j^{\delta(j)}) - z_i \tau_i \right] \quad (3)$$

where z_i is the indicator of arbitration on T_i : $z_i = 1$ if the platform has consulted for arbitration on T_i ; $z_i = 0$ otherwise. τ_i is the corresponding arbitration fee. We assume that τ_i is a value known by all providers, requesters, and the platform. For each $(R_i, P_j) \in \mathcal{W}$, we define

$$U(R_i, P_j) = (w_i^R - \bar{\beta}_i) + (w_j^P - \bar{\alpha}_j^{\delta(j)}) - z_i \tau_i \quad (4)$$

which is the portion of platform utility contributed by (R_i, P_j) . Clearly, $U = \sum_{(R_i, P_j) \in \mathcal{W}} U(R_i, P_j)$.

Remark 1: The utilities of providers, requesters, and the auctioneer in this paper are different from those in [35]. Another difference between this paper and [35] is that we model the postauction process into an extensive-form game, in contrast to a simultaneous game. \square

The notations of this paper are summarized in Table I.

TABLE I
NOTATIONS

Symbol	Meaning
R_i, P_j	Provider (seller), requester (buyer)
\mathcal{R}, \mathcal{P}	The set of providers, requesters
T_i	R_i 's task
v_i	Valuation of T_i
\mathbf{b}/b_i	Bid vector/bid from R_i
\mathbf{c}_j/c_j^i	Cost vector of P_j /cost of P_j to finish T_i
$\mathbb{A}/\mathbf{a}_j/a_j^i$	Ask matrix/ask vector of P_j /ask of P_j to finish T_i
\mathcal{W}	Set of winning provider-requester pairs
$\delta(\cdot)$	Assignment function from providers to requesters
β_i	Payment of R_i from the auction
$\boldsymbol{\beta}$	Payment vector for requesters from the auction
α_j^i	Payment of P_j for T_i from the auction
$\boldsymbol{\alpha}_j$	Payment vector of P_j from the auction
α	Payment matrix of providers from the auction
\mathbb{M}	The auction mechanism
$U_i^R/U_j^P/U$	Utility of R_i/P_j /the platform
x_i	Indicator of T_i 's status
$y_j^{\delta(j)}$	Indicator of P_j 's devotion on $T_{\delta(j)}$
z_i	Indicator of arbitration on T_i
τ_i	Arbitration fee of T_i
$\bar{\beta}_i$	Final payment that R_i receives from the platform
$\bar{\alpha}_j^{\delta(j)}$	Final payment that P_j receives from the platform

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

In this section, we present a crowdsourcing mechanism EFF, which, with the help from a trusted third party for arbitration, eliminates free-riding and false-reporting and incentivizes each provider to complete the assigned task.

A. Description of EFF

In EFF, a trustworthy third party, who can provide arbitration on the status of T_i with an arbitration fee $\tau_i > 0$, is available.

The first part of EFF applies auction \mathbb{M} , where \mathcal{W} , $\boldsymbol{\beta}$, and $\boldsymbol{\alpha}$ are decided. After the auction, the platform collects a warranty $w_i^R = \beta_i + \tau_i$ from R_i and a warranty $w_j^P = \theta\alpha_j^i + \tau_i$ from P_j for each $(R_i, P_j) \in \mathcal{W}$, where $\theta > 0$ is a system parameter. We use $\theta\alpha_j^i$ to help incentivize P_j to complete T_i . If P_j has been assigned to work on T_i but does not complete T_i , it will receive a penalty of $\theta\alpha_j^i$.

After R_i and P_j submitted their warranties, an extensive-form game is applied. P_j decides whether or not to work on T_i . If P_j chooses to devote effort on T_i , T_i would be completed. Otherwise, T_i is incomplete with no effort devoted by P_j . Then, R_i and P_j submit their independent reports on the status of T_i . Gathering the reports from R_i and P_j , the platform decides the final payments $\bar{\beta}_i$ and $\bar{\alpha}_j^i$ for R_i and P_j , respectively. The formal description of EFF is presented as Algorithm 1.

With the payments $\bar{\beta}_i$ and $\bar{\alpha}_j^i$ from Algorithm 1, utilities of R_i and P_j can be computed based on (1) and (2), respectively. These utility values are shown in Table II. The first row indicates P_j 's effort on T_i and the second row lists the reports from P_j . The first column lists the reports from R_i . For each of the two-tuples, the first element is the utility of R_i , and the second element is the utility of P_j .

We pick two entries in Table II and explain how the corresponding utilities are derived. First, we explain the entry where

Algorithm 1. EFF

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1   $(\mathcal{W}, \boldsymbol{\beta}, \boldsymbol{\alpha}) \leftarrow \mathbb{M}(\mathbf{b}, \mathbb{A});$ 
2   $\forall (R_i, P_j) \in \mathcal{W}, w_i^R \leftarrow \tau_i + \beta_i, w_j^P \leftarrow \tau_i + \theta\alpha_j^i;$ 
3   $R_i$  submits  $w_i^R$  and  $P_j$  submits  $w_j^P$  to the platform;
4   $\bar{\beta}_i \leftarrow w_i^R; \bar{\alpha}_j^i \leftarrow w_j^P;$ 
5   $P_j$  decides whether or not to work on  $T_i$ , and devotes the
   corresponding effort;
6   $R_i$  and  $P_j$  submit independent reports on the status of  $T_i$  to
   the platform;
7  if Reports are different then
8      The platform consults arbitration for the status of  $T_i$ ,
       and pays  $\tau_i$  to the arbitrator;
9      if  $R_i$  submits a false report then
10          $\bar{\beta}_i \leftarrow \bar{\beta}_i - \tau_i;$ 
11     else
12          $\bar{\alpha}_j^i \leftarrow \bar{\alpha}_j^i - \tau_i;$ 
13     end
14 else
15     The platform adopts the reports from  $R_i$  and  $P_j$ ;
16 end
17 if The platform concludes that  $T_i$  is completed then
18      $\bar{\beta}_i \leftarrow \bar{\beta}_i - \beta_i; \bar{\alpha}_j^i \leftarrow \bar{\alpha}_j^i + \alpha_j^i;$ 
19     // The auction payment is made
20 else
21      $\bar{\alpha}_j^i \leftarrow \bar{\alpha}_j^i - \theta\alpha_j^i;$ 
22     //  $\theta\alpha_j^i$  is taken from  $P_j$  for not completing  $T_i$ 
23 end
24 The platform returns  $\bar{\beta}_i$  to  $R_i$  and  $\bar{\alpha}_j^i$  to  $P_j$ , respectively.

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T_i is completed, and both R_i and P_j submit **C** (marked in red in Table II). In line 2 of Algorithm 1, we have $w_i^R = \tau_i + \beta_i$ and $w_j^P = \tau_i + \theta\alpha_j^i$. In line 4, we have $\bar{\beta}_i = \tau_i + \beta_i$ and $\bar{\alpha}_j^i = \tau_i + \theta\alpha_j^i$. Because both R_i and P_j submit **C**, no arbitration is consulted, and the platform concludes that T_i is completed. Thus, $\bar{\beta}_i = (\tau_i + \beta_i) - \beta_i = \tau_i$. Since P_j has devoted effort on T_i and T_i is completed, we have $y_j^i = 1$ and $x_i = 1$. In line 18, we have $\bar{\alpha}_j^i = (\tau_i + \theta\alpha_j^i) + \alpha_j^i$. Based on (1) and (2), R_i 's utility is $v_i - \beta_i$ and P_j 's utility is $\alpha_j^i - c_j^i$. Next, we explain the entry where T_i is incomplete, R_i submits **I**, and P_j submits **C** (marked in blue in Table II). In line 2, we have $w_i^R = \tau_i + \beta_i$ and $w_j^P = \tau_i + \theta\alpha_j^i$. In line 4, we have $\bar{\beta}_i = \tau_i + \beta_i$ and $\bar{\alpha}_j^i = \tau_i + \theta\alpha_j^i$. Because R_i and P_j submit different reports, an arbitration is consulted and the arbitration result indicates that P_j submits the dishonest report. In line 12, we have $\bar{\alpha}_j^i = (\tau_i + \theta\alpha_j^i) - \tau_i = \theta\alpha_j^i$. Because T_i is incomplete, we have $y_j^i = 0$, $x_i = 0$. In line 20, we have $\bar{\alpha}_j^i = \theta\alpha_j^i - \theta\alpha_j^i = 0$. Based on (1) and (2), R_i 's utility is 0 and P_j 's utility is $-\theta\alpha_j^i - \tau_i$.

According to Table II, there is a unique SPE. If P_j completes T_i , P_j would report **C** regardless of what R_i reports. Since P_j reports **C**, R_i prefers reporting **C** to reporting **I**. Hence, if P_j completes T_i , both R_i and P_j would report **C**. For similar reason, if P_j does not complete T_i , both R_i and P_j would report **I**. Comparing the utilities of P_j when completing T_i (which is

TABLE II
UTILITIES OF R_i AND P_j IN EFF FOR $(R_i, P_j) \in \mathcal{W}$, THE ENTRY FOR THE UNIQUE SPE IS MARKED BY \checkmark

$R_i \backslash P_j$	T_i completed		T_i not completed	
	C	I	C	I
C	$(v_i - \beta_i, \alpha_j^i - c_j^i) \checkmark$	$(v_i - \beta_i, \alpha_j^i - c_j^i - \tau_i)$	$(-\beta_j, \alpha_j^i)$	$(-\tau_i, -\theta\alpha_j^i)$
I	$(v_i - \beta_i - \tau_i, \alpha_j^i - c_j^i)$	$(v_i, -\theta\alpha_j^i - c_j^i)$	$(0, -\theta\alpha_j^i - \tau_i)$	$(0, -\theta\alpha_j^i)$

$\alpha_j^i - c_j^i > 0$) and not completing T_i (which is $-\theta\alpha_j^i < 0$), P_j prefers completing T_i . Thus, the unique SPE is reached when P_j completes T_i , and both R_i and P_j submit **C**.

B. Analysis of EFF

In this section, we prove several properties of EFF.

Theorem 1: EFF eliminates free-riding and false-reporting, while guaranteeing truthfulness, transaction-wise budget-balance, and computational efficiency. \square

To prove this theorem, we need to prove Lemmas 1–3. Recall that auction \mathbb{M} is individually rational, transaction-wise budget-balanced, computationally efficient, and truthful.

Lemma 1: EFF eliminates free-riding and false-reporting, while guaranteeing truthfulness. \square

Proof: Suppose that (R_i, P_j) is in \mathcal{W} when R_i bids v_i and P_j bids c_j . The unique SPE is achieved when P_j completes T_i and both R_i and P_j submit **C**. According to Table II and the individual rationality of \mathbb{M} , R_i 's utility is $v_i - \beta_i \geq 0$ and P_j 's utility is $\alpha_j^i - c_j^i \geq 0$. When R_i or P_j changes its bid during the auction, due to the truthfulness of \mathbb{M} , the corresponding payment of R_i could not be lower than β_i and the corresponding payment of P_j could not be higher than α_j^i . Thus, neither R_i nor P_j has incentive to change its bid. When R_i submits **I** for false-reporting, P_j still reports **C** since it is P_j 's dominant strategy when T_i is completed. R_i 's corresponding utility would be $v_i - \beta_i - \tau_i < v_i - \beta_i$. When P_j chooses not to complete T_i but submits **C** for free-riding, R_i still reports **I** since it is R_i 's dominant strategy when T_i is incomplete. P_j 's corresponding utility would be $-\theta\alpha_j^i - \tau_i < 0 \leq \alpha_j^i - c_j^i$. Thus, neither R_i nor P_j could benefit from being dishonest.

Suppose that R_i loses the auction by bidding $b_i = v_i$. Its utility is 0. Suppose that R_i changes its bid. If R_i still loses the auction, its utility remains to be 0. If R_i wins the auction, its new payment in the auction β_i is no smaller than v_i since \mathbb{M} is truthful. If T_i is completed, according to Table II, R_i 's utility is no more than $v_i - \beta_i \leq v_i - b_i = 0$ since P_j would always report **C**. If T_i is incomplete, R_i could not have a positive utility. Thus, R_i could not benefit from being dishonest.

Suppose that P_j loses the auction by asking $a_j = c_j$. Its utility is 0. Suppose that P_j changes its ask. If P_j still loses the auction, its utility remains to be 0. If P_j wins the auction and is assigned to complete T_i , P_j 's new payment in the auction α_j^i is no larger than c_j^i since \mathbb{M} is truthful. If P_j completes T_i , according to Table II, its utility is no larger than $\alpha_j^i - c_j^i \leq a_j^i - c_j^i = 0$. If P_j does not complete T_i , its utility is no more than $-\theta\alpha_j^i \leq 0$ since R_i would report **I**. Thus, P_j could not benefit from being dishonest.

To sum up all cases, EFF eliminates free-riding and false-reporting, while guaranteeing truthfulness. \blacksquare

Remark 2: By Lemma 1, dishonest behaviors are eliminated in EFF. According to the unique SPE in the extensive-form game in EFF, for each $(R_i, P_j) \in \mathcal{W}$, P_j would finish T_i , which indicates that EFF incentivizes each winning provider to complete its assigned task. \square

Lemma 2: EFF is transaction-wise budget-balanced. \square

Proof: Note that by the transaction-wise budget-balance of \mathbb{M} , $\beta_i - \alpha_j^i \geq 0$ for each $(R_i, P_j) \in \mathcal{W}$. We prove this lemma by the following case analysis.

- 1) If R_i and P_j both submit **C**, the platform believes that T_i is completed without consulting for arbitration. Thus, we have $\bar{\beta}_i = \tau_i$ and $\bar{\alpha}_j^i = \tau_i + (1 + \theta)\alpha_j^i$. By (4), we have $U(R_i, P_j) = \beta_i - \alpha_j^i \geq 0$.
- 2) If R_i and P_j both submit **I**, the platform believes that T_i is incomplete without consulting for arbitration. Thus, we have $\bar{\beta}_i = \tau_i + \beta_i$ and $\bar{\alpha}_j^i = \tau_i$. By (4), we have $U(R_i, P_j) = \theta\alpha_j^i \geq 0$.
- 3) If R_i submits **C** and P_j submits **I** when T_i is completed, the platform consults for arbitration, and the result shows that P_j lies in the report. Thus, we have $\bar{\beta}_i = \tau_i + \beta_i$ and $\bar{\alpha}_j^i = (1 + \theta)\alpha_j^i$. By (4), we have $U(R_i, P_j) = \beta_i - \alpha_j^i \geq 0$.
- 4) If R_i submits **C** and P_j submits **I** when T_i is incomplete, the platform consults for arbitration, and the result shows that R_i lies in the report. Thus, we have $\bar{\beta}_i = \beta_i$ and $\bar{\alpha}_j^i = \tau_i$. By (4), we have $U(R_i, P_j) = \theta\alpha_j^i \geq 0$.
- 5) If R_i submits **I** and P_j submits **C** when T_i is completed, the platform consults for arbitration, and the result shows that R_i lies in the report. Thus, we have $\bar{\beta}_i = 0$ and $\bar{\alpha}_j^i = \tau_i + (1 + \theta)\alpha_j^i$. By (4), we have $U(R_i, P_j) = \beta_i - \alpha_j^i \geq 0$.
- 6) If R_i submits **I** and P_j submits **C** when T_i is incomplete, the platform consults for arbitration, and the result shows that P_j lies in the report. Thus, we have $\bar{\beta}_i = \tau_i + \beta_i$ and $\bar{\alpha}_j^i = 0$. By (4), we have $U(R_i, P_j) = \theta\alpha_j^i \geq 0$.

Thus, EFF is transaction-wise budget-balanced. \blacksquare

Lemma 3: EFF is computationally efficient. \square

Proof: Since \mathbb{M} is computationally efficient, and report submission, arbitration, and pricing all take constant time, EFF is computationally efficient. \blacksquare

Lemmas 1–3 complete the proof for Theorem 1.

Remark 3: EFF is not individually rational. To incentivize each winning provider to complete its assigned task, we impose a penalty $\theta\alpha_j^i$ in Algorithm 1, line 20. If P_j fails to complete T_i but behaves honestly, its utility is $-\theta\alpha_j^i < 0$, which violates individual rationality. However, this incentivizes P_j to complete

the task. This part differs from that in [35], where no such penalty is imposed and individual rationality is achieved. \square

V. DFF: DISCOURAGING FREE-RIDING AND FALSE-REPORTING WITHOUT ARBITRATION

EFF successfully eliminates free-riding and false-reporting with the help from a trusted third party for arbitration. However, it is not true that an arbitration is always available. In this section, we present another mechanism DFF, which, without any arbitration, discourages free-riding and false-reporting, while still guaranteeing several economic properties.

A. Description of DFF

Same as EFF, the first part of DFF applies the auction \mathbb{M} . For each $(R_i, P_j) \in \mathcal{W}$, DFF collects a warranty $w_i^R = (1 + \zeta)\beta_i$ from R_i and a warranty $w_j^P = (\zeta + \eta)\alpha_j^i$ from P_j , where $\zeta > 0$ and $\eta > 0$ are system parameters. In DFF, we use ζ to help discourage dishonest behavior, and η to help incentivize providers to complete their assigned tasks.

After the auction, R_i and P_j pay their warranties to the platform. We model the postauction part of DFF as another extensive-form game. P_j first decides whether or not to work on T_i , and devotes the corresponding effort. Then both R_i and P_j submit their independent reports on the status of T_i . With the reports from R_i and P_j , the platform decides the final payments $\bar{\beta}_i$ and $\bar{\alpha}_j^i$ for each of the following cases.

- 1) When R_i and P_j both submit **C**, we have $\bar{\beta}_i = \zeta\beta_i$ and $\bar{\alpha}_j^i = (\zeta + \eta)\alpha_j^i + \alpha_j^i$. This means that R_i pays β_i to the platform and P_j receives α_j^i from the platform.
- 2) When R_i and P_j both submit **I**, we have $\bar{\beta}_i = (1 + \zeta)\beta_i$ and $\bar{\alpha}_j^i = \zeta\alpha_j^i$. This means that R_i pays nothing to the platform and P_j pays $\eta\alpha_j^i$ to the platform.
- 3) When R_i submits **C** and P_j submits **I**, we have $\bar{\beta}_i = \zeta\beta_i$ and $\bar{\alpha}_j^i = \zeta\alpha_j^i$. This means that R_i pays β_i to the platform and P_j pays $\eta\alpha_j^i$ to the platform.
- 4) When R_i submits **I** and P_j submits **C**, we have $\bar{\beta}_i = 0$ and $\bar{\alpha}_j^i = 0$. This means that R_i pays $(1 + \zeta)\beta_i$ to the platform and P_j pays $(\zeta + \eta)\alpha_j^i$ to the platform.

The formal description of DFF is presented as Algorithm 2.

Based on the final payments $\bar{\beta}_i$ and $\bar{\alpha}_j^i$ from Algorithm 2, utilities of R_i and P_j can be computed based on (1) and (2), respectively. These utility values are shown in Table III. Notations in Table III represent similar meanings as those in Table II.

We pick two entries and explain how the corresponding utilities are derived. First, we explain the entry where T_i is completed and both R_i and P_j submit **C** (marked in red in Table III). In line 2 of Algorithm 2, we have $w_i^R = (1 + \zeta)\beta_i$ and $w_j^P = (\zeta + \eta)\alpha_j^i$. In line 4, we have $\bar{\beta}_i = (1 + \zeta)\beta_i$ and $\bar{\alpha}_j^i = (\zeta + \eta)\alpha_j^i$. Because both R_i and P_j submit **C**, in line 8, we have $\bar{\beta}_i = (1 + \zeta)\beta_i - \beta_i = \zeta\beta_i$ and $\bar{\alpha}_j^i = (\zeta + \eta)\alpha_j^i + \alpha_j^i$. Since P_j has devoted effort on T_i and T_i is completed, we have $y_j^i = 1$ and $x_i = 1$. Based on (1) and (2), R_i 's utility is $v_i - \beta_i$ and P_j 's utility is $\alpha_j^i - c_j^i$. Next, we explain the

Algorithm 2. DFF

- 1 $(\mathcal{W}, \beta, \alpha) \leftarrow \mathbb{M}(\mathbf{b}, \mathbb{A});$
 - 2 $\forall (R_i, P_j) \in \mathcal{W}, w_i^R \leftarrow (1 + \zeta)\beta_i, w_j^P \leftarrow (\zeta + \eta)\alpha_j^i;$
 - 3 R_i submits w_i^R and P_j submits w_j^P to the platform;
 - 4 $\bar{\beta}_i \leftarrow w_i^R; \bar{\alpha}_j^i \leftarrow w_j^P;$
 - 5 P_j decides whether or not to work on T_i , and devotes the corresponding effort;
 - 6 R_i and P_j submit independent reports on the status of T_i to the platform;
 - 7 **if** (Both R_i and P_j submit **C**) **then**
 - 8 | $\bar{\beta}_i \leftarrow \bar{\beta}_i - \beta_i; \bar{\alpha}_j^i \leftarrow \bar{\alpha}_j^i + \alpha_j^i;$
 - 9 **else if** (Both R_i and P_j submit **I**) **then**
 - 10 | $\bar{\alpha}_j^i \leftarrow \bar{\alpha}_j^i - \eta\alpha_j^i;$
 - 11 **else if** (R_i submits **C** and P_j submits **I**) **then**
 - 12 | $\bar{\beta}_i \leftarrow \bar{\beta}_i - \beta_i; \bar{\alpha}_j^i \leftarrow \bar{\alpha}_j^i - \eta\alpha_j^i;$
 - 13 **else**
 - 14 | $\bar{\beta}_i \leftarrow \bar{\beta}_i - (1 + \zeta)\beta_i; \bar{\alpha}_j^i \leftarrow \bar{\alpha}_j^i - (\zeta + \eta)\alpha_j^i;$
 - 15 **end**
 - 16 The platform returns $\bar{\beta}_i$ to R_i and $\bar{\alpha}_j^i$ to P_j , respectively.
-

entry where T_i is incomplete, R_i submits **I**, and P_j submits **C** (marked in blue in Table III). In line 2, we have $w_i^R = (1 + \zeta)\beta_i$ and $w_j^P = (\zeta + \eta)\alpha_j^i$. In line 4, we have $\bar{\beta}_i = (1 + \zeta)\beta_i$ and $\bar{\alpha}_j^i = (\zeta + \eta)\alpha_j^i$. Because R_i submits **I** and P_j submits **C**, in line 14, we have $\bar{\beta}_i = (1 + \zeta)\beta_i - (1 + \zeta)\beta_i = 0$ and $\bar{\alpha}_j^i = (\zeta + \eta)\alpha_j^i - (\zeta + \eta)\alpha_j^i = 0$. Because T_i is incomplete, we have $y_j^i = 0$ and $x_i = 0$. Based on (1) and (2), R_i 's utility is $-\beta_i - \zeta\beta_i$ and P_j 's utility is $-\zeta\alpha_j^i - \eta\alpha_j^i$.

B. Analysis of DFF

In this section, we introduce the definition of semi-truthfulness and prove several properties of DFF.

Definition 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. \square

Comparing the definitions of semi-truthfulness and truthfulness, semi-truthfulness requires a stronger requirement, assuming that the other individuals are honest, while truthfulness has no such assumption.

Theorem 2: DFF is semi-truthful, transaction-wise budget-balanced, and computationally efficient. \square

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

Lemma 4: DFF is semi-truthful. \square

Proof: Suppose that (R_i, P_j) is in \mathcal{W} when R_i bids v_i and P_j bids c_j . If P_j completes T_i and no individual lies, 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 that R_i bids a value deviating from v_i , it will not pay a lower payment due to the truthfulness of \mathbb{M} . If R_i lies by reporting **I** instead of **C**, and P_j does not lie and reports **C**, R_i 's utility would be $v_i - (1 + \zeta)\beta_i' \leq v_i - (1 + \zeta)\beta_i \leq v_i - \beta_i$, where β_i' is the corresponding payment after R_i changes its bid. Thus, R_i has no incentive to lie when T_i is completed and P_j is honest. For P_j , by deviating its ask from c_j , it will not receive a higher payment. If P_j lies by reporting **I**, and R_i does not lie and

TABLE III
UTILITIES OF R_i AND P_j IN DFF FOR EACH $(R_i, P_j) \in \mathcal{W}$, THE ENTRY FOR EACH EQUILIBRIUM IS MARKED BY \checkmark

$R_i \backslash P_j$	T_i completed		T_i not completed	
	C	I	C	I
C	$(v_i - \beta_i, \alpha_j^i - c_j^i) \checkmark$	$(v_i - \beta_i, -c_j^i - \eta\alpha_j^i)$	$(-\beta_i, \alpha_j^i)$	$(-\beta_i, -\eta\alpha_j^i)$
I	$(v_i - \beta_i - \zeta\beta_i, -c_j^i - \zeta\alpha_j^i - \eta\alpha_j^i)$	$(v_i, -c_j^i - \eta\alpha_j^i)$	$(-\beta_i - \zeta\beta_i, -\zeta\alpha_j^i - \eta\alpha_j^i) \checkmark$	$(0, -\eta\alpha_j^i)$

reports **C**, P_j 's corresponding utility would be $-\eta\alpha_j^i - c_j^i \leq \alpha_j^i - c_j^i \leq \alpha_j^i - c_j^i$, where α_j^i is the corresponding payment of P_j after P_j changes its bid. Thus, P_j has no incentive to lie when T_i is completed and R_i is honest. If P_j chooses not to complete T_i and reports **I** honestly, its utility would be $-\eta\alpha_j^i < 0$. If P_j reports **C** dishonestly, since R_i is honest and reports **I**, P_j 's utility would be $-(\eta + \zeta)\alpha_j^i < 0$. Thus, P_j would complete T_i . Therefore, if R_i or P_j knows that the other one is honest, it would be honest.

Suppose that R_i loses the auction by bidding $b_i = v_i$. Its original utility is 0. Suppose that R_i changes its bid. If it still loses the auction, its utility remains to be 0. If it wins the auction and P_j is assigned to T_i , R_i 's payment in the auction β_i is no smaller than v_i since \mathbb{M} is truthful. If T_i is completed, according to Table II, R_i 's utility is no larger than $v_i - \beta_i \leq v_i - b_i = 0$ since P_j is honest and reports **C**. If T_i is incomplete, R_i could not have a positive utility. Thus, R_i could not benefit from unilaterally being dishonest.

Suppose that P_j loses the auction by asking $\mathbf{a}_j = \mathbf{c}_j$. Its original utility is 0. Suppose that P_j changes its ask. If it still loses the auction, its utility remains to be 0. If it wins the auction and is assigned to T_i , P_j 's payment in the auction α_j^i is no larger than c_j^i since \mathbb{M} is truthful. If P_j completes T_i , according to Table II, its utility is no larger than $\alpha_j^i - c_j^i \leq \alpha_j^i - c_j^i = 0$. If P_j does not complete T_i , its utility is no more than $-\theta\alpha_j^i \leq 0$ since R_i is honest and reports **I**. Thus, P_j could not benefit from unilaterally being dishonest.

To sum up all cases, DFF is semi-truthful. \blacksquare

Remark 4: With semi-truthfulness, we know that there is one equilibrium left in correspondence with each status of T_i . If P_j completes T_i , both R_i and P_j would report **C**. If P_j does not complete T_i , both R_i and P_j would report **I**. Comparing these two equilibria, P_j has a utility of $\alpha_j^i - c_j^i > 0$ in the first equilibrium, and a utility of $-\eta\alpha_j^i < 0$ in the second one. Thus, P_j prefers to complete T_i , which makes the first equilibrium the unique SPE and encourages all winning providers to complete their assigned tasks, while discouraging free-riding and false-reporting. Note that in [35], the simultaneous game computes two equilibria with no preference of P_j to complete T_i or not. However, by applying the extensive-form game instead of the simultaneous game, we have one unique SPE which incentivizes all winning providers to complete the tasks and discourages dishonest behaviors. \square

Lemma 5: DFF is transaction-wise budget-balanced. \square

Proof: Since \mathbb{M} is transaction-wise budget-balanced, we have $\beta_i \geq \alpha_j^i$ for each $(R_i, P_j) \in \mathcal{W}$. If both R_i and P_j submit **C**, the platform utility generated from this winning pair

is $U(R_i, P_j) = \beta_i - \alpha_j^i \geq 0$. If R_i submits **I** and P_j submits **C**, $U(R_i, P_j) = (1 + \zeta)\beta_i + (\zeta + \eta)\alpha_j^i \geq 0$. If R_i submits **C** and P_j submits **I**, $U(R_i, P_j) = \beta_i + \eta\alpha_j^i \geq 0$. If both of them submit **I**, $U(R_i, P_j) = \eta\alpha_j^i \geq 0$. Thus, DFF is transaction-wise budget-balanced. \blacksquare

Lemma 6: DFF is computationally efficient. \square

The proof is the same as that of Lemma 3 since the two mechanisms have the same time complexity.

Lemmas 4–6 complete the proof for Theorem 2.

Remark 5: Truthfulness is not guaranteed by DFF. For instance, when T_i is incomplete and R_i reports **C**, P_j may benefit by reporting **C** dishonestly instead of reporting **I**. Individual rationality is another economic property that DFF does not guarantee. Because when T_i is incomplete and P_j lies, R_i 's utility is negative even if R_i reports honestly. \square

VI. PERFORMANCE EVALUATION

To evaluate the performance of EFF and DFF, we implemented both mechanisms, and carried out extensive testing on various cases. In both EFF and DFF, we used TASC [33] as the auction mechanism \mathbb{M} . We chose maximum matching algorithm [30] as the bipartite matching algorithm used in TASC. The tests were run on a PC with a 3.5-GHz CPU, and 16-GB memory.

Remark 6: TASC [33] is a double auction-based incentive mechanism proposed for cooperative communication, where the relay nodes offer relay services for rewards. TASC is truthful, individually rational, transaction-wise budget-balanced, and computationally efficient. TASC consists of two major steps. 1) It applies a bid-independent bipartite matching algorithm to compute an assignment from the buyers to the sellers. 2) It applies the McAfee [21] double auction to determine final payments for all buyers and sellers. \square

Performance metrics: We first studied the impact of the size of users on the running time as a demonstration of computational efficiency, and compare the running time of EFF and DFF with that of TASC. We next studied the impact of the size of users and user behavior on the platform utility. Finally, we studied the utilities of providers and requesters.

A. Simulation Setup

For EFF, we set $\tau_i = 10$ for all T_i and $\theta = 0.1$. For DFF, we set $\zeta = 0.6$ and $\eta = 0.1$. Note that this setting is for simplicity only. For properties of τ_i , θ , ζ , and η , see Sections IV and V, respectively. Valuations, costs, bids, and asks are uniformly

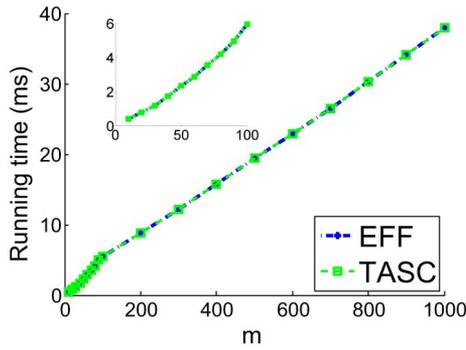


Fig. 1. Running time of EFF and TASC with $n = 100$.

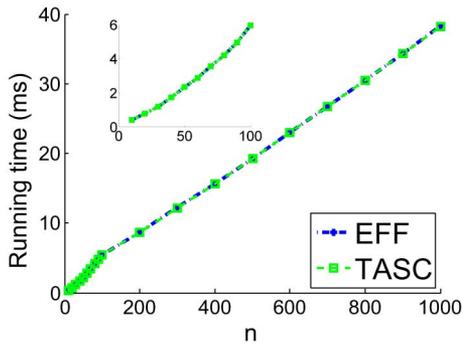


Fig. 2. Running time of EFF and TASC with $m = 100$.

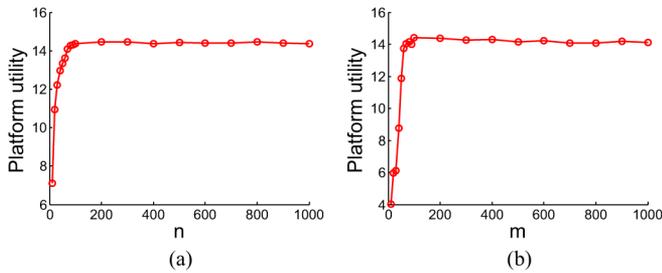


Fig. 3. Platform utility in EFF: (a) $m = 100$, (b) $n = 100$.

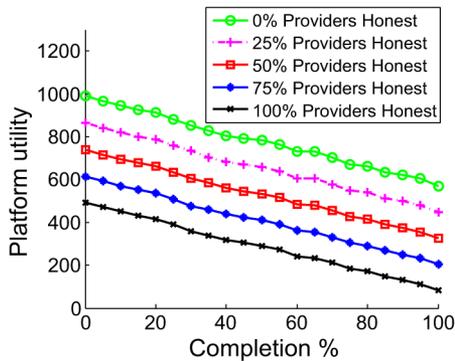


Fig. 4. Platform utilities in DFF with honest requesters, $\eta = 0.1$ and $\zeta = 0.6$.

distributed over $[0, 20]$. All results in Figs. 1–8 are averaged over 50 000 runs for each configuration.

To study the behavior of the running time as a function of the number of users, we first fixed $m = 100$ and let n increase from 10 to 1000; then we fixed $n = 100$ and let m increase from 10

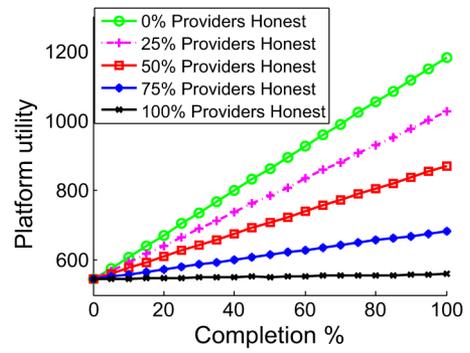


Fig. 5. Platform utilities in DFF with honest requesters, $\eta = 0.3$ and $\zeta = 4$.

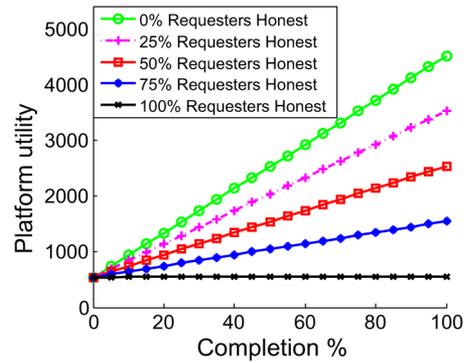


Fig. 6. Platform utilities in DFF when all providers are honest.

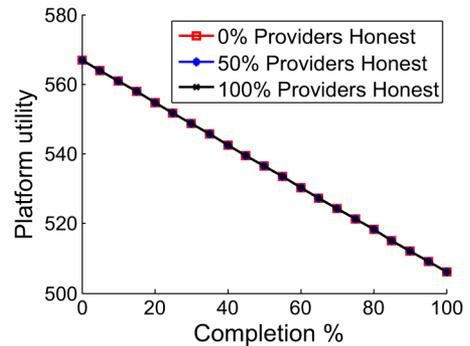


Fig. 7. Platform utilities in EFF with honest providers.

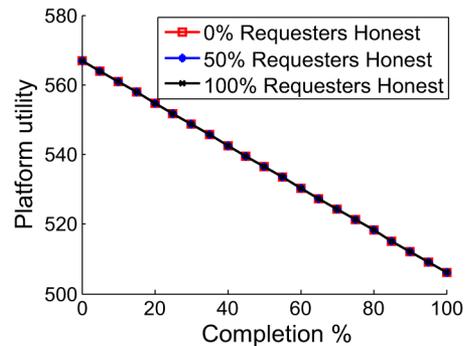


Fig. 8. Platform utilities in EFF with honest requesters.

to 1000. The corresponding results are reported in Figs. 1 and 2, respectively.

To study the behavior of the platform utility as a function of the number of users, we first fixed $m = 100$ and let n increase

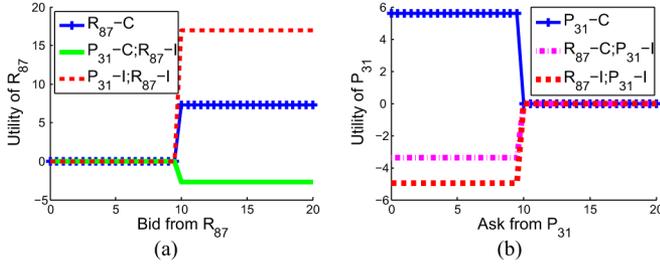


Fig. 9. Completed tasks in EFF: (a) Utility of R_{87} , (b) utility of P_{31} .

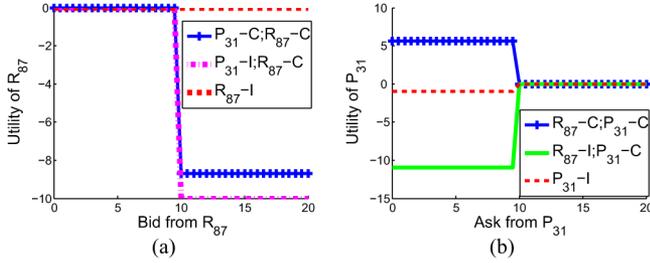


Fig. 10. Incomplete tasks in EFF: (a) Utility of R_{87} , (b) utility of P_{31} .

from 10 to 1000; then we fixed $n = 100$ and let m increase from 10 to 1000. We chose the scenario where all providers complete their tasks and all individuals are honest (we will present the impact of dishonest users with incomplete tasks on the platform utilities later). In this case, according to Algorithm 1, Algorithm 2, and (3), the platform utilities in EFF and DFF are the same. Thus, we only show the platform utilities in EFF, and the corresponding results are reported in Fig. 3.

To study the platform utility as a function of the percentage of completed tasks in DFF, we fixed $m = 100$ and $n = 100$, and let the percentage of completed tasks vary from 0% to 100% with an increment of 5%. To study the impact of the number of honest users (who submit honest reports) on platform utility, we first set all requesters to be honest and monitor different percentages of honest providers with different system parameter values of η and ζ in Figs. 4 and 5, respectively. Then, we set all providers to be honest, and monitor different percentages of honest requesters in Fig. 6.

To study the platform utility as a function of the percentage of completed tasks in EFF, we fixed $m = 100$ and $n = 100$, and let the percentage of completed tasks varies from 0% to 100% with an increment of 5%. The corresponding results are presented in Figs. 7 and 8.

To study the utilities of requesters and providers, we set $m = n = 100$, and ran both EFF and DFF. The corresponding results are reported in Figs. 9–12, where R_{87} is a randomly picked requester and P_{31} is the corresponding provider, with $v_{87} = 17$, $c_{31}^{87} = 4$. R_{87} is matched up with P_{31} by the maximum matching algorithm.

B. Simulation Results

1) *Running Time:* We study the impact of the size of users on the running time as a demonstration of computational efficiency. Since EFF and DFF have the same running time, we

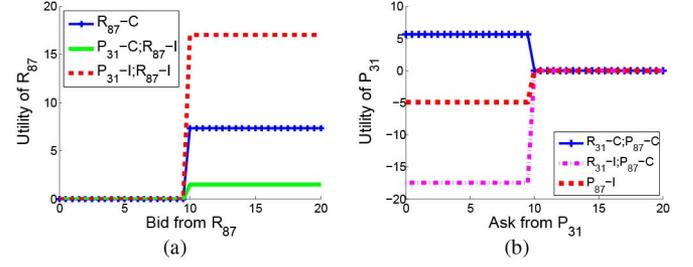


Fig. 11. Completed tasks in DFF: (a) Utility of R_{87} , (b) utility of P_{31} .

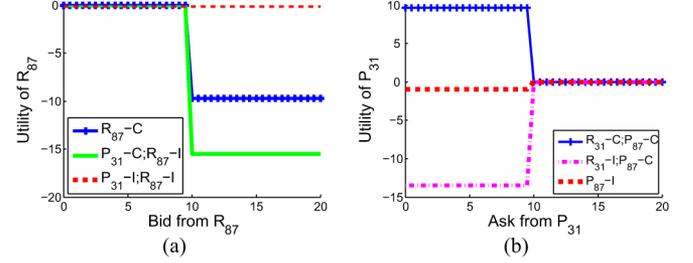


Fig. 12. Incomplete tasks in DFF: (a) Utility of R_{87} , (b) utility of P_{31} .

only show the running time of EFF. From Fig. 1, we observe that with the increase of m , the running time increases quadratically when $m < n$, then grows linearly when $m > n$. This is because the first part of TASC is a bipartite matching algorithm [30], which takes $O(\min\{m, n\} \times |E|)$ time, where $|E|$ is the number of edges in the graph and is bounded by $O(mn)$. Let $l = \min\{m, n\}$. The total time complexity is $O(l|E| + l \log l)$. Thus, in Fig. 1, when $m < n = 100$, the running time is $O(m^2)$; when $m > n = 100$, the running time is $O(m)$. Fig. 2 can be interpreted by a similar approach. Comparing Figs. 1 and 2, we observe that the impact from m and n is almost the same. Another observation is that the running time of EFF is almost the same as that of TASC, which implies that applying EFF or DFF does not introduce a high computation cost to ML.

2) *Platform Utility:* We study the platform utility of EFF as a function of the number of providers and requesters in Fig. 3. We observe that the platform utility is nonnegative, which is guaranteed by the transaction-wise budget-balance of EFF. The platform utility increases at first, then stays steady when $m > 100$. This is because the platform utility depends on not only the final payments but also $|\mathcal{W}|$, which is bounded by $\min\{m, n\}$. Therefore, when $m < n$, $|\mathcal{W}|$ increases and the platform utility increases. When $|\mathcal{W}|$ reaches $\min\{m, n\}$, the platform utility stays at a steady level. Since in this scenario, the platform utilities in EFF and DFF are the same, we only show the platform utilities in EFF.

We study the impact of user behavior on the platform utility in DFF. The results are presented in Figs. 4–6, respectively. In Figs. 4 and 5, we observe that when all requesters are honest in DFF, with the increasing percentage of completed tasks, the platform utility decreases. This is because with more tasks completed, the platform collects less penalties from providers for incomplete tasks. However, in Fig. 5 where we set $\eta = 0.3$ and $\zeta = 4$, with the increasing percentage of completed tasks, the platform utility increases. This is because with more completed

tasks, the platform collects more penalties from the situation where providers are lying on their reports. Comparing Figs. 4 and 5, the different trends are due to different system parameter values. Since it is not the major concern of this paper on how to set the values for τ_i , η , and ζ , we do not provide theoretical analysis on the impact of τ_i , η , and ζ on the platform utility. In Figs. 4–6, we can observe that with more honest users, the platform utility decreases. This is because when R_i and P_j both behave honestly for each $(R_i, P_j) \in \mathcal{W}$, the platform would not collect penalties from them for being dishonest.

Fig. 6 shows the platform utilities of EFF as a function of the number of completed tasks, and it can be interpreted by a similar approach as that of Fig. 5. However, it can be proved theoretically that changing system constants η and ζ would not change the increasing trend in Fig. 6. Since it is not the major concern in this paper, we do not show the analysis here.

We study the impact of user behavior on the platform utility in EFF, and the results are shown in Figs. 7 and 8, respectively. We observe that when all requesters are honest in EFF, with the increasing percentage of the completed tasks, the platform utility decreases. This is because with more tasks completed, the platform collects less penalties from the providers for incomplete tasks. Another observation is that the number of honest users does not have an impact on the platform utility. This is because in EFF, if an individual submits a dishonest report, it pays τ_i to the platform. However, the platform needs to pay τ_i for arbitration. Thus, the number of honest users does not influence the platform utility in EFF.

3) *Individual Utility*: We monitor the utilities of R_{87} and P_{31} in EFF. Fig. 9 shows the utilities of R_{87} and P_{31} , where P_{31} completed the assigned task in EFF. From Fig. 9, we observe that neither R_{87} nor P_{31} can have a utility higher than that it has when bidding $b_{87} = v_{87} = 17$ and asking $a_{31}^{87} = c_{31}^{87} = 4$. From Fig. 9(b), we observe that reporting **C** is the dominant strategy for P_{31} . According to Fig. 9(a), R_{87} would report **C** when P_{31} reports **C**. Thus, both R_{87} and P_{31} would report **C**.

Fig. 10 shows the utilities when P_{31} does not complete the task in EFF. Again, we observe that no individual can get a positive utility increment by being dishonest using a similar analysis approach. Hence, both R_{87} and P_{31} would report **I**.

Comparing the utilities of P_{31} in EFF when it completes the task and when it does not complete the task (represented by the blue line in Fig. 9(b) and the red line in Fig. 10(b)), P_{31} would choose to complete the task for a higher utility.

Next we monitor the utilities of R_{87} and P_{31} in DFF. From Fig. 11, we observe that when P_{31} completes the task, there is no incentive for an individual to be dishonest when the other is honest. Thus, both R_{87} and P_{31} would report **C**.

Fig. 12 shows the semi-truthfulness when P_{31} fails to complete the task in DFF. Again, we observe that there is no incentive for an individual to be dishonest when the other is honest. Hence, both R_{87} and P_{31} would report **I**.

Comparing the utilities of P_{31} in DFF when it completes the task and when it does not complete the task (represented by the blue line in Fig. 11(b) and the red line in Fig. 12(b), respectively), P_{31} would choose to complete the task for a higher utility.

VII. CONCLUSION

In this paper, we proposed two novel mechanisms to tackle free-riding and false-reporting in crowdsourcing. We first presented EFF and proved that with arbitration, EFF eliminates free-riding and false-reporting, while guaranteeing truthfulness, transaction-wise budget-balance, and computational efficiency. We then presented DFF and proved that without arbitration, DFF is semi-truthful, while guaranteeing transaction-wise budget-balance and computational efficiency. Another feature of our mechanisms is that providers are incentivized to complete their assigned tasks. We implemented both EFF and DFF. Extensive numerical results are presented to study the performance of our proposed mechanisms.

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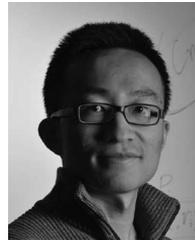
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