Fairness-Aware Auction Mechanism for Sustainable Mobile Crowdsensing

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Abstract. With the proliferation of sensor-embedded mobile devices, mobile crowdsensing has become a paradigm of significant interest. Incentivizing sensory-data providers to keep sustainability in a mobile crowdsensing system is a critical issue nowadays, and auction-based mechanisms have been proposed to motivate providers via monetary rewards. In our work, this sustainability problem is formulated as an optimization problem maximizing providers' proportionally fair utilities with respect to their multi-dimensional fairness factors, and a fairness-aware auction mechanism is designed accordingly. To the best of our knowledge, this is the first work that considers multi-dimensional fairness of providers as the objective in selecting providers for the mobile crowdsensing system. In addition, we present rigorous theoretical analysis proving that our mechanism meets budget feasibility, individual rationality and truthfulness. Finally, simulations are performed to demonstrate the performance of our proposed mechanism.

1 Introduction

Nowadays the number of mobile devices is significantly increased. It is predicted that the number of mobile users will reach 4.68 billion in 2019 [1]. The increasing of mobile users provides an economic way to collect huge amount of information, *e.g.*, companies can hire mobile users to collect data from their mobiles' sensors, such as cameras and accelerometers instead of deploying actual sensors that has a comparable higher cost. Such a mobile crowdsensing system has many practical and valuable usage; for examples, estimate road surface condition [2], detect heat stroke [3], predict traffic condition [4], collect daily weather conditions [5], gather signal and Wi-Fi information at a specific location [6], and maximize influence in location-based social networks [7], etc.

To ensure the performance of mobile crowdsensing, a large number of providers are needed to collect sensory data. But mobile users are often reluctant to serve as providers due to resource limitation (*e.g.*, battery, bandwidth, memory, etc.) and potential privacy leakage [10–13,24,25], unless they can gain

satisfying rewards as compensation. Another issue in mobile corwdsensing is that some providers submit low-quality data to the system to gain rewards easily, which has a highly negative effect on the applications using the collected data. To solve these issues, many incentive mechanisms have been proposed to select providers to guarantee providers receiving non negative utilities even when there is a big number of providers [14,23].

Most of the existing works mainly focused on monetary-incentive and quality-aware mechanisms motivating mobile users to stay in the mobile crowdsensing system with high-quality sensory data provided in a short term [8,9,15] without caring about long-term sustainability of the system. Notice that in mobile crowdsensing, each provider has different bid price, data quality, and performance history. The system should take these information into consideration, otherwise high-quality providers with higher bids might quit from the system due to lost in multiple rounds. For instance, a provider has lost for 4–5 rounds in the auction and still keep losing due to his high bid price, and he might think that he/she does not have a chance to win in this system. If he loses again, then he might lose interest and leave the system. As a result, eventually the system will have only a few providers who keep winning in many rounds, and these providers can bid any price since there is no competitor anymore, hindering the sustainable development of mobile crowdsensing in a long-term period. Therefore, sustainability should be one critical property of the mobile crowdsensing system for long-term economic and social benefits.

As significant as sustainability is in the mobile corwdsensing system, there are only a few state-of-art works that mentioned how to achieve sustainability [16,18]. There exists a mechanism proposed to maintain sustainability but that mechanism considers only data quality [18]. Motivated by these observation, in this paper, our goal is to develop an incentive mechanism to enhance sustainability by taking multi-dimensional fairness into consideration. To achieve this property, the problem of provider selection is mathematically formulated as an optimization problem with proportional fairness as the objective function, in which the fairness factor is quantified from three aspects, including data quality, lost frequency, and submission time of each provider. Since the optimization problem is NP-Hard, it takes a very long time to obtain the optimal results. Hence, an auction-based greedy algorithm (*i.e.*, our fairness-aware auction mechanism) is utilized to solve the problem. Through rigorous theoretical proofs, we show that our proposed auction mechanism can simultaneously achieve individual rationality, budget feasibility, and truthfulness. Moreover, our simulations validate that our proposed auction mechanism can outperform the existing mechanisms in a long term in terms of sustainability, fairness and data quality. To sum up, the contributions of this paper are as follows:

– To the best of our knowledge, this is the first work to consider multi-dimensional fairness for data provider selection in the mobile crowdsensing system, and such problem is formulated into an optimization problem to achieve proportional fairness.
– A fairness-aware auction mechanism is designed to incentivize providers to stay in the mobile crowdsensing system in a long-term period,

– Theoretical analysis is performed to show that the auction mechanism can guarantee individual rationality, budget feasibility, and truthfulness.
– Comprehensive simulations are conducted to verify the effectiveness of our proposed auction mechanism.

The remainder of this paper is organized as follows. Existing works are briefly describes in Sect. 2. The mobile crowdsensing system model and problem formulation are explained in Sect. 3. The proposed fairness-aware auction mechanism is illustrated in Sect. 4. In addition, the performance evaluation is demonstrated in Sect. 5. Finally, we give a conclusion in Sect. 6.

2   Related Work

Incentive mechanisms are critical for mobile crowdsensing to attract providers and requesters, in which auction has been a widely studied model to motivate users.

Instead of only aiming at attracting mobile users for sensing activities in a short term, recent research have been focusing on how to motivate mobile users to stay in a mobile crowdsensing system for a long term, which is called sustainability. For example, Luo *et al.* [16] surveyed how to make mobile crowdsensing systems sustainable by utilizing three schemes: auctions, lotteries and trust and reputation systems. In [17], Ni *et al.* suggested solutions for fog-based vehicular crowdsensing to reach sustainability. The solutions are that the platform needs to provide security, privacy and fairness to both general users and sensing providers. In addition, Sun *et al.* [18] proposed a mechanism, in which the selection process and payment determination mainly depends on providers' qualities such that the system will be sustainable in a long run with sufficient incentives.

To keep sustainability in mobile crowdsensing systems, fairness is an important factor that has been considered. For instance, in [19], Zhu *et al.* designed an auction-based solution to address free-riding problem and also claimed that the solution can provide fairness for users and improve the quality of works. Huang *et al.* [20] developed a double auction mechanism with considering the fairness among data consumers. Moreover, in [21], Duan *et al.* proposed a mechanism for IoT-based mobile crowdsensing systems considering fairness among providers such that each provider receives a reward with respect to his effort.

Unlike the existing works, this paper is the first one that take into account multi-dimensional fairness of data providers (*i.e.*, mobile users) for auctions in mobile crowdsensing systems, where providers can be selected by considering their data quality, lost frequency, and submission time for sustainability improvement of mobile crowdsensing.

3   System Model and Problem Formulation

Auction Model. The mobile crowdsensing system consisting of a cloud service and a number of mobile users equipped with sensors on their mobile devices.

The cloud service acts as a requester demanding task implementation, and the mobile users act as providers processing tasks, in which there are more providers than tasks. In this paper, we consider a real scenario where auction mechanism is performed in multi-round during a long-term period. In each round, the providers compete for task implementation, and the requester determines the winners and their payments. After collecting sensory data from the winners, the requester records the information of task completion (including data quality, submission time, and others) and uses it for managing auction in the next round.

Assume that there are m providers, denoted by $\Gamma = \{\gamma_1, \gamma_2, ..., \gamma_m\}$, and n tasks, denoted by $\Delta = \{\delta_1, \delta_2, ..., \delta_n\}$. For these n tasks, each provider i ($1 \leq i \leq m$) a bidding profile $b_i^t = \{b_{i1}^t, b_{i2}^t, ..., b_{in}^t\}$ where b_{ij}^t is the bid of provider i for task j ($1 \leq j \leq n$) in round t, and the requester has his value profile $V = \{v_1, v_2, ..., v_n\}$ where v_j is the value of task j. Additionally, the requester has a budget B to purchase task service from the providers. Let p_{ij}^t be the payment paid to provider i for processing task j in round t. Thus, in each round, the total payment paid from the requester cannot exceed B, i.e., $\sum_{i=1}^{m} \sum_{j=1}^{n} x_{ij}^t p_{ij}^t \leq B$, and each provider i's utility is $u_{ij}^t = x_{ij}^t(p_{ij}^t - b_{ij}^t)$, where $x_{ij}^t \in \{0, 1\}$ is the winner determination variable.

Fairness Factor. To keep sustainability of the mobile crowdsensing system, a multi-dimensional fairness factor is quantified from the following three aspects.

(1) *Data Quality.* High-quality data is critical to improve the performance of mobile crowdsensing. The providers who submit higher-quality data should be better considered than the ones with lower-quality data. For example, provider i always measures temperature more accurately than provider j does; hence, provider i deserves to be selected with a higher probability. The data quality of provider i in round t is represented by q_i^t, and the normalized data quality $\overline{q}_i^t$ can be computed as $\overline{q}_i^t = \frac{q_i^t}{max_{i' \in [1, ..., m]} \ q_{i'}^t}$.

(2) *Lost Frequency.* A provider may lose interest in mobile crowdsensing if he loses too many times in auctions. Thus, to maintain attractiveness to the providers, the number of losing rounds, denoted by l_i^t, and the number of consecutively losing rounds, denoted by c_i^t, should be taken into account. Accordingly, the normalized number of losing rounds is $\overline{l}_i^t = \frac{l_i^t}{max_{i' \in [1, ..., m]} \ l_{i'}^t}$, and the normalized number of consecutively losing rounds is $\overline{c}_i^t = \frac{c_i^t}{max_{i' \in [1, ..., m]} \ c_{i'}^t}$.

(3) *Submission Time.* Since some requests may be time-sensitive, submitting data late could cause requester in trouble. For example, the requester would like to know a traffic on a street at a specific time to find a route to go to his destination in time, but if the requester obtains this information late, he has to make a decision by himself without the help of the sensory data. In this case, the received data becomes useless. Therefore, there should be some punishments for the providers who submit data late. Suppose the average late submission of provider i in round t is a_i^t that can be updated

in every round as $a_i^t = \frac{a_i^{t-1}(t-1) + max(0, s_i^t - d_i^t)}{t}$, where s_i^t is the submission time of provider i in round t and d_i^t is the submission deadline assigned to provider i in round t. Moreover, the normalized late submission is $\overline{a}_i^t = 1 - \frac{a_i^t}{max_{i' \in [1,...,m]} a_{i'}^t}$.

By combining the aforementioned aspects, an assignment score for each provider i in round t is computed as $\omega_i^t = \alpha_1 \overline{q}_i^t + \alpha_2 \overline{l}_i^t + \alpha_4 \overline{c}_i^t + \alpha_4 \overline{a}_i^t$, where α_i ($1 \le i \le 4$) indicates the weight of each corresponding aspect, and $\alpha_1 + \alpha_2 + \alpha_3 + \alpha_4 = 1$. To compare all the providers' scores, the fairness factor of provider i in round t can be determined as $f_i^t = \omega_i^t / \sum_{i'=1}^{m} \omega_{i'}^t$.

Optimization Problem. In this paper, our problem can be mathematically expressed in Eq. (1a), (1b), (1c), (1d), (1e) and (1f).

$$\max \quad \sum_{t=1}^{T} \sum_{i=1}^{m} \sum_{j=1}^{n} f_i^t \log(1 + u_{ij}^t); \tag{1a}$$

$$\text{s.t.} \quad \sum_{i=1}^{m} x_{ij}^t \le 1, 1 \le j \le n; \tag{1b}$$

$$\sum_{j=1}^{n} x_{ij}^t \le 1, 1 \le i \le m; \tag{1c}$$

$$\sum_{i=1}^{m} \sum_{j=1}^{n} p_{ij}^t \le B; \tag{1d}$$

$$x_{ij}^t \in \{0, 1\}, 1 \le i \le m, 1 \le j \le n, 1 \le t \le T; \tag{1e}$$

$$p_{ij}^t \ge 0, 1 \le i \le m, 1 \le j \le n, 1 \le t \le T. \tag{1f}$$

In (1a), (1b), (1c), (1d), (1e) and (1f), our objective is to maintain proportional fairness for all the providers in mobile crowdsensing during a long-term period. The constraints in Eqs. (1b) and (1c) respectively mean each task is process by at most one provider and each provider is allowed to carry out at most one task. The budget constraint is indicated by Eq. (1d). The ranges of variables are implied by Eqs. (1e) and (1f).

Furthermore, our auction mechanism based on Eq. (1a), (1b), (1c), (1d), (1e) and (1f) aims to satisfy the following economic properties [14]. (i) *Individual Rationality*: an auction can achieve this property when no provider obtains a negative utility, *i.e.*, $u_{ij}^t \ge 0$. (ii) *Truthfulness*: an auction is truthful when the best strategy for each provider is to report his true bid, *i.e.*, $p_{ij}^t - b_{ij}^t \ge p_{ij}'^t - b_{ij}'^t$ where b_{ij}^t is the true bid and $p_{ij}'^t$ is the payment for the untruthful bid $b_{ij}'^t$. (iii) *Budget Feasibility*: the total payment for providers cannot exceed the budget of the requester.

4   Fairness-Aware Auction Mechanism

In this section, our auction mechanism for Eq. (1a), (1b), (1c), (1d), (1e) and (1f) will be detailed, in which the winners are determined by the allocation rule and the payments are calculated by the pricing rule.

4.1   Allocation Rule

The requester selects providers based on the fairness factors, the bids and the budget. Since at first, the providers' payments and utilities are unknown, we estimate the contributions provider i makes to the auction objective using $O_{ij}^t = f_i^t \log(1 + v_j q_i^t)$. Let M be a set of pairs (γ_i, δ_j), where for each pair (γ_i, δ_j) with $b_{ij}^t \neq 0$, $\gamma_i = \arg\max_{\gamma_{i'} \in \Gamma} O_{i'j}^t$. In M, the pairs are sorted in a non-increasing order according to $R_{ij}^t = \frac{O_{ij}^t}{b_{ij}^t}$. The construction of set M is described in line 11 of Algorithm 1. Without lose of generality, we assume that in $M = \{(\gamma_{i^1}, \delta_{j^1}), (\gamma_{i^2}, \delta_{j^2}), \cdots, (\gamma_{i^{|M|}}, \delta_{j^{|M|}})\}$, $R_{i^1 j^1}^t \geq R_{i^2 j^2}^t \geq \cdots \geq R_{i^{|M|} j^{|M|}}^t$.

Let W be the set of pairs of selected providers (*i.e.*, winners) and their assigned tasks. Next, the requester picks pairs from M one by one to W in order until pair $(\gamma_{i^k}, \delta_{j^k})$ cannot satisfy the budget condition:

$$b_{i^k j^k}^t \leq \frac{O_{i^k j^k}^t \cdot B}{O_{i^k j^k}^t + \sum\limits_{(\gamma_{i^w}, \delta_{j^w}) \in W} O_{i^w j^w}^t}. \tag{2}$$

4.2   Pricing Rule

Initially, all the payments are set to be 0. Then, the selected provider i^k assigned to task j^k in set W is paid with the amount according to (3).

$$p_{i^k j^k}^t = \min\{\frac{O_{i^k j^k}^t \cdot B}{\sum\limits_{(\gamma_{i^w}, \delta_{j^w}) \in W} O_{i^w j^w}^t}, \frac{O_{i^k j^k}^t}{R_{i^{|W|} j^{|W|}}^t}\}. \tag{3}$$

where $R_{i^{|W|} j^{|W|}}^t$ is the smallest ratio among the pairs in W.

The pseudo codes of our auction mechanism are presented in Algorithm 1.

4.3   Theoretical Analysis

Lemma 1. *If* $b_{i^k j^k}^t \leq \frac{O_{i^k j^k}^t \cdot B}{\sum\limits_{(\gamma_{i^w}, \delta_{j^w}) \in W} O_{i^w j^w}^t}$, *then* $b_{i^{k-1} j^{k-1}}^t \leq \frac{O_{i^{k-1} j^{k-1}}^t \cdot B}{\sum\limits_{(\gamma_{i^w}, \delta_{j^w}) \in W} O_{i^w j^w}^t}$ *where* $(\gamma_{i^k}, \delta_{j^k}) \in W$ *and* $k \geq 2$.

Proof. This lemma can be proved from the definition of R_{ij}^t and Eq. (2). $\square$

Lemma 2. *Every pair* $(\gamma_{i^k}, \delta_{j^k})$ *in* W *can satisfy* $b_{i^k j^k}^t \leq \frac{O_{i^k j^k}^t \cdot B}{\sum\limits_{(\gamma_{i^w}, \delta_{j^w}) \in W} O_{i^w j^w}^t}$.

Algorithm 1. Fairness-Aware Auction Mechanism

Require: $\{f_i^t\}$, $\{b_{ij}^t\}$, Γ, B, V, Δ
1: **for** $i = 0, 1, 2, ..., m$ **do**
2:   **for** $j = 0, 1, 2, ..., n$ **do**
3:     $p_{ij}^t = 0, x_{ij}^t = 0$
4:     **if** $b_{ij}^t == 0$ **then**
5:       $\hat{u}_{ij}^t = 0, O_{ij}^t = 0, R_{ij}^t = 0$
6:     **else**
7:       $\hat{u}_{ij}^t = v_j \cdot q_i^t, O_{ij}^t = f_i^t \cdot log(1 + \hat{u}_{ij}^t), R_{ij}^t = \frac{O_{ij}^t}{b_{ij}^t}$
8:     **end if**
9:   **end for**
10: **end for**
11: $M \leftarrow$ ProviderSelection($\{O_{ij}^t\}, \Gamma, \Delta$), $W \leftarrow \emptyset$, $k = 1$
12: Sort members in M in non-increasing order with respect to R_{ij}^t
13: **while** $k \leq |M|$ **do**
14:   **if** $b_{i^k j^k}^t \leq \frac{O_{i^k j^k}^t \cdot B}{O_{i^k j^k}^t + \sum\limits_{(\gamma_{i^w}, \delta_{j^w}) \in W} O_{i^w j^w}^t}$ **then**
15:     $W \leftarrow (\gamma_{i^k}, \delta_{j^k}), x_{i^k j^k}^t = 1$
16:   **else**
17:     break
18:   **end if**
19:   $k = k + 1$
20: **end while**
21: **for** $k = 1$ to $|W|$ **do**
22:   $p_{i^k j^k}^t = min(\frac{O_{i^k j^k}^t \cdot B}{\sum\limits_{(\gamma_{i^w}, \delta_{j^w}) \in W} O_{i^w j^w}^t}, \frac{O_{i^k j^k}^t}{R_{i^{|W|} j^{|W|}}^t})$
23: **end for**
24: **return** $\{x_{ij}^t\}, \{p_{ij}^t\}$

Proof. This lemma can hold based on Lemma 1 and and Eq. (2). □

Lemma 3. *Every pair* $(\gamma_{i^k}, \delta_{j^k})$ *in* W *satisfies* $b_{i^k j^k}^t \leq \frac{O_{i^k j^k}^t}{R_{i^{|W|} j^{|W|}}^t} = \frac{O_{i^k j^k}^t b_{i^{|W|} j^{|W|}}^t}{O_{i^{|W|} j^{|W|}}^t}$.

Proof. According to Lemma 2, this conclusion can hold. □

Theorem 1. *Our auction mechanism is individually rational for all providers.*

Proof. According to Lemmas 2 and 3, for any $(\gamma_{i^k}, \delta_{j^k})$ in W, we have $b_{i^k j^k}^t \leq p_{i^k j^k}^t = min(\frac{O_{i^k j^k}^t \cdot B}{\sum\limits_{(\gamma_{i^w}, \delta_{j^w}) \in W} O_{i^w j^w}^t}, \frac{O_{i^k j^k}^t b_{i^{|W|} j^{|W|}}^t}{O_{i^{|W|} j^{|W|}}^t})$. Therefore, $u_{ij}^t \geq 0$. □

Lemma 4. *The proposed auction mechanism satisfies monotone allocation.*

Proof. If γ_i wins with b_{ij}^t and submits $b_{ij}'^t < b_{ij}^t$, then γ_i with $b_{ij}'^t$ also wins because $b_{ij}'^t < b_{ij}^t \leq \dfrac{O_{ij}^t \cdot B}{O_{ij}^t + \sum\limits_{(\gamma_{iw}, \delta_{jw}) \in W} O_{i_w j_w}^t}$. □

Lemma 5. *For each provider i, p_{ij}^t is the critical value to process task j.*

Proof. Note that p_{ij}^t is the critical value if and only if γ_i wins when $b_{ij}^t \leq p_{ij}^t$ and loses when $b_{ij}^t > p_{ij}^t$. From the allocation and pricing rules, we have

(i) Case $b_{ij}^t \leq p_{ij}^t$: $b_{ij}^t \leq \dfrac{O_{ij}^t \cdot B}{\sum\limits_{(\gamma_{iw}, \delta_{jw}) \in W} O_{i_w j_w}^t}$, and $\dfrac{O_{ij}^t}{b_{ij}^t} \geq \dfrac{O_{i|W|j|W|}^t}{b_{i|W|j|W|}^t}$; thus, γ_i wins.

(ii) Case $b_{ij}^t > p_{ij}^t$: $b_{ij}^t > \dfrac{O_{ij}^t \cdot B}{\sum\limits_{(\gamma_{iw}, \delta_{jw}) \in W} O_{i_w j_w}^t}$ or $\dfrac{O_{ij}^t}{b_{ij}^t} < \dfrac{O_{i|W|j|W|}^t}{b_{i|W|j|W|}^t}$; thus γ_i loses.

In summary, γ_i has p_{ij}^t as the critical value. □

Theorem 2. *The proposed auction mechanism satisfies truthfulness.*

Proof. According to [22], since the allocation is monotone (Lemma 4) and the payment of each winner is the critical value (Lemma 5), the auction mechanism can guarantee truthfulness. □

Theorem 3. *The auction scheme can meet budget feasibility.*

Proof. From Eq. (3), the total payment is at most $\sum\limits_{(\gamma_i, \delta_j) \in W} p_{ij}^t = \dfrac{\sum_{(\gamma_i, \delta_j) \in W} O_{ij}^t B}{\sum_{(\gamma_i, \delta_j) \in W} O_{ij}^t}$ $= B$. If any γ_i receives payment $\dfrac{O_{ij}^t}{R_{i|W|j|W|}^t}$, then the total payment does not exceed B as $\dfrac{O_{ij}^t}{R_{i|W|j|W|}^t} \leq \dfrac{O_{ij}^t \cdot B}{\sum\limits_{(\gamma_i, \delta_j) \in W} O_{ij}^t}$. Therefore, this mechanism is budget feasible. □

5   Performance Evaluation

5.1   Simulation Setting

To evaluate the performance of our fairness-aware auction mechanism (termed FM), two other auction mechanisms are compared in the simulations, including: (i) Budget Feasible Auction Mechanism (termed BFAM) [23]: this mechanism sets budget feasibility as a constraint of the auction but is not equal to fairness-awareness. (ii) Practical Incentive Mechanism (termed PIM) [21]: this mechanism considers fairness among providers as the objective function such that each provider should gain the benefit according to his work.

In the comparison, the performance metrics contain the number of remaining providers, the average data quality, the providers' cumulative average utilities and total payment. In our setting, each provider has his own range of bids so that in each round, he can randomly pick his bidding price from the range,
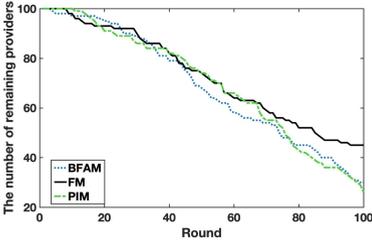
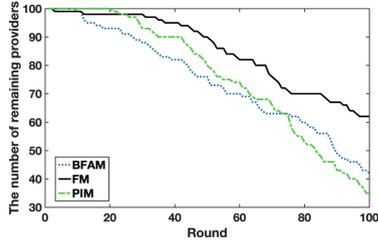**Fig. 1.** Number of remaining providers with $B = 200$, $m = 100$, and $n = 60$

Fig. 2. Number of remaining providers with $B = 1000$, $m = 100$, and $n = 60$
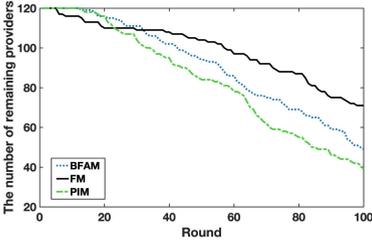

Fig. 3. Number of remaining providers with $B = 1500$, $m = 120$, and $n = 60$
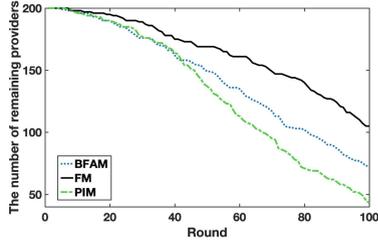

Fig. 4. Number of remaining providers with $B = 1500$, $m = 200$, and $n = 60$

and the fairness factor is updated in every round. At the end of each round, the losers have certain probabilities to quit the mechanism, and the probability of provider i is $\eta_i^t = \frac{\lambda l_i^t + (1-\lambda)c_i^t}{\lambda L + (1-\lambda)C}$, where $\lambda \in [0,1]$ implies the importance of the number of losing rounds compared with the number of consecutive losing rounds, L and C are respectively the maximum number of losing rounds and the maximum number of consecutive losing rounds a provider can tolerate. The system parameters are: $\alpha_1 = 0.2, \alpha_2 = 0.3, \alpha_3 = 0.1$, and $\alpha_4 = 0.4$.

5.2   Simulation Results

The key goal of this paper is to improve sustainability of mobile crowdsensing, which is measured by the number of remaining providers and the fairness index in the long term.

Figures 1 and 2 show the number of remaining providers along with the increasing rounds and different budgets. As can be seen in the figures, when the budget increases, the gap between the number of remaining providers of PIM and that of FM at round 100 becomes wider. Since PIM does not consider fairness, mostly the same providers are selected as winners in each round; hence, many providers happen to lose in many rounds and quit from mobile crowdsensing system. On the other hand, by taking fairness into account, FM provides more chances to providers who have lost for many rounds; thus, those providers
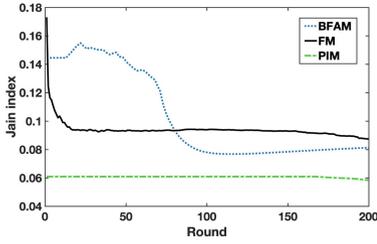
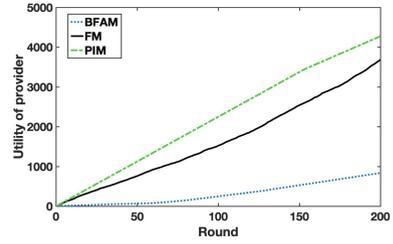**Fig. 5.** Jain's index with $B = 1500$, $m = 100$ and $n = 60$

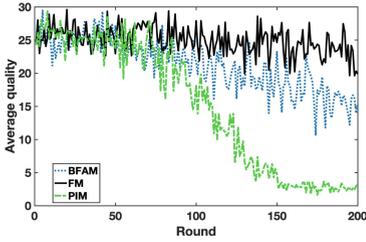**Fig. 6.** Cumulative average utility with $B = 1500$, $m = 100$ and $n = 60$

Fig. 7. Average quality of different mechanisms with $B = 1500$, $m = 100$ and $n = 60$
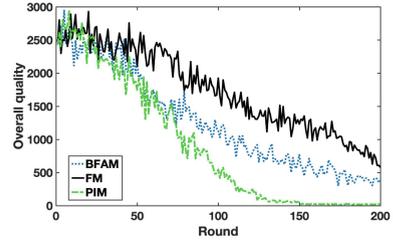

Fig. 8. Overall quality of different mechanisms with $B = 1500$, $m = 100$ and $n = 60$

are still willing to stay in the system. In addition, the increase of budget leads FM to be able to select more providers, and then fewer providers leave.

In Figs. 3 and 4, the number of remaining providers is presented with the increasing rounds and different number of providers (m). As m goes up, the gap between the number of remaining providers of FM and that of PIM in round 100 also becomes bigger. This is because the winners from PIM are mostly the same in every round, the rest of providers rarely have a chance to win; therefore, they give up and quit. In contrast, the providers who lost in prior rounds have more chances to win with their fairness factors in FM.

Jain's index is a factor ranging in $[0, 1]$ and used to measure how fair the mechanisms are for providers; specifically, a larger value of Jain's index indicates a higher degree of fariness. Figure 5 shows the jain's index of different auction mechanisms at each round. At the beginning, BFAM has the higher Jain's index than our proposed mechanism; however, at the certain point, it drops lower than our proposed mechanism because BFAM keeps selecting the same winners. On the other hand, FM outperforms PIM as PIM does not take fairness in the long term into account.

In Fig. 6, the cumulative average utility of providers is shown with the increasing rounds. One can observe that the cumulative average utility from BFAM is the lowest, and the one from FM is the highest. Notice that the number of winners from BFAM is quite constant and in contrary, the one from FM varies with

fairness factor in each round. As a result, some providers with high bid prices can still win in FM due to their high fairness factors, obtaining higher utilities.

We assume that the quality of each provider is stable. Initially, the range of quality is randomly set from a uniform distribution for the providers. Figure 7 shows the average data quality of the winners in each round. At first, the average data qualities are the same in all auction mechanisms. However, since FM considers the providers' data qualities as one component of their fairness factors, the average data quality of FM grows up above the average data qualities of BFAM and PIM in the late rounds. Additionally, BFAM and PIM cause many providers to quit from the system; hence, the system does not have many available providers to select, reducing the average data qualities.

The overall data qualities of the winners in different auction mechanism are presented in Fig. 8. The overall data qualities of the three mechanisms decrease round by round because in each round, some high-quality providers may leave the system. However, FM can still outperform the others in term of the overall data quality, for which the reason is the same as that for Fig. 7.

6   Conclusion

We propose a fairness-aware auction mechanism for improving sustainability of mobile crowdsensing systems. Our work is different from state-of-art work as we take multi-dimensional fairness into account to guarantee the incentivized mobile users stay in the system in a long run. Then we perform rigorous theoretical analysis proving that our proposed auction mechanism is budget feasible, individually rational and truthful. Finally, our simulation results clearly demonstrate the improvement of effectiveness compared to the existing works.

References

1. https://www.statista.com/statistics/274774/forecast-of-mobile-phone-users-worldwide/
2. Ikeda, Y., Inoue, M.: An estimation of road surface conditions using participatory sensing. In: International Conference on Electronics, Information, and Communication (ICEIC), pp. 1–3, January 2018
3. Ismail, M.Z., Inoue, M.: Map generation to detect heat stroke by using participatory sensing data. In: International Conference on Electronics, Information, and Communication (ICEIC), pp. 1–4, January 2018
4. Waze Mobile. https://www.waze.com
5. WeatherLah, BuUuk Pte Ltd. http://www.weatherlah.com/
6. OpenSignal. http://opensignal.com/

7. Li, J., Cai, Z., Yan, M., Li, Y.: Using crowdsourced data in location-based social networks to explore influence maximization. In: INFOCOM, April 2016
8. Li, J., Cai, Z., Wang, J., Han, M., Li, Y.: Truthful incentive mechanisms for geographical position conflicting mobile crowdsensing systems. IEEE Trans. Comput. Soc. Syst. **5**, 324–334 (2018)
9. Wang, Y., Cai, Z., Zhan, Z., Gong, Y., Tong, X.: An optimization and auction based incentive mechanism to maximize social welfare for mobile crowdsourcing. IEEE Trans. Comput. Soc. Syst. 1–16 (2019, early access)
10. Cai, Z., Zheng, X., Yu, J.: A differential-private framework for urban traffic flows estimation via taxi companies. IEEE Trans. Ind. Inf. (2019, accepted)
11. Cai, Z., Zheng, X.: A private and efficient mechanism for data uploading in smart cyber-physical systems. IEEE Trans. Netw. Sci. Eng. (2018, early access)
12. Wang, Y., Cai, Z., Tong, X., Gao, Y.: Truthful incentive mechanism with location privacy-preserving for mobile crowdsourcing systems. Comput. Netw. **135**, 32–43 (2018)
13. Wang, Y., Cai, Z., Yin, G., Gao, Y., Tong, X., Wu, G.: An incentive mechanism with privacy protection in mobile crowdsourcing systems. Comput. Netw. **102**, 157–171 (2016)
14. Zhang, X., Yang, Z., Liu, Y., Li, J., Ming, Z.: Toward efficient mechanisms for mobile crowdsensing. IEEE Trans. Veh. Technol. **66**, 1760–1771 (2017)
15. Wang, H., Guo, S., Cao, J., Guo, M.: MELODY: a long-term dynamic quality-aware incentive mechanism for crowdsourcing. IEEE Trans. Parallel Distrib. Syst. **29**, 901–914 (2017)
16. Luo, T., Kanhere, S.S., Huang, J., Das, S.K., Wu, F.: Sustainable incentives for mobile crowdsensing: auctions, lotteries, and trust and reputation systems. IEEE Commun. Mag. **55**, 68–74 (2017)
17. Ni, J., Zhang, A., Lin, X., She, X.S.: Security, privacy, and fairness in fog-based vehicular crowdsensing. IEEE Commun. Mag. **55**, 146–162 (2017)
18. Sun, X., Li, J., Zheng, W., Liu, H.: Towards a sustainable incentive mechanism for participatory sensing. In: IEEE First International Conference on Internet-of-Things Design and Implementation (IoTDI), pp. 49–60, April 2016
19. Zhu, X., An, J., Yang, M., Xiang, L., Yang, Q., Gui, X.: A fair incentive mechanism for crowdsourcing in crowd sensing. IEEE Internet Things J. **3**, 1364–1372 (2016)
20. Huang, H., Xin, Y., Sun, Y., Yang, W.: A truthful double auction mechanism for crowdsensing systems with max-min fairness. In: IEEE Wireless Communications and Networking Conference (WCNC), pp. 1–6, March 2017
21. Duan, Z., Tian, L., Yan, M., Cai, Z., Han, Q., Yin, G.: Practical incentive mechanisms for IoT-based mobile crowdsensing systems. IEEE Access **5**, 20383–20392 (2017)
22. Myerson, R.: Optimal auction design. Math. Oper. Res. **6**(1), 58–73 (1981)
23. Singer, Y.: Budget feasible mechanisms. In: IEEE 51st Annual Symposium on Foundations of Computer Science (FOCS), pp. 765–774, October 2010
24. Liu, C.-C., Wang, S., Ma, L., Cheng, X., Bie, R., Yu, J.: Mechanism design games for thwarting malicious behavior in crowdsourcing applications. In: INFOCOM, April 2017
25. Capurso, N., Mei, B., Song, T., Cheng, X., Jiguo, Y.: A survey on key fields of context awareness for mobile devices. J. Netw. Comput. Appl. **118**, 44–60 (2018)