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Improving Both Quantity and Quality: Incentive Mechanism for Social Mobile Crowdsensing Architecture

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ABSTRACT Mobile crowdsensing has emerged as an efficient paradigm for performing large-scale sensing tasks. Improving both the quantity and quality of users is still the pivotal problem for mobile crowdsensing system. This paper gives a comprehensive solution to improve the quantity and quality of users simultaneously through the social mobile crowdsensing architecture. To incentive the users based on the novel architecture, we first propose a universal initial diffuser selection algorithm to accommodate two widely studied diffusion models and, then a lightweight, multi-metric comprehensive, and parameter-free user quality evaluation method is presented. Finally, we propose a reverse auction to optimize the new criterion, which takes both social cost and user quality into consideration. Through both rigorous theoretical analysis and extensive simulations, we demonstrate that the proposed incentive mechanisms achieve computational efficiency, individual rationality, truthfulness, and guaranteed approximation. Meanwhile, the proposed incentive mechanisms show prominent advantage in total unit quality cost and running time.

INDEX TERMS Influence diffusion, crowdsensing, incentive mechanism, social network.

I. INTRODUCTION

In the last few years, the market of smartphone has proliferated rapidly, and smartphones become almost indispensable to our lives. Now smartphones are integrated with a variety of sensors such as camera, light sensor, GPS, accelerometer, digital compass, gyroscope, microphone, and proximity sensor. Additionally, the emergence of wearable sensors significantly expands the sensing capabilities. Most sensors can connect to smartphones via interface for data sharing. These sensors carried by users can sense various human activities and the surrounding environment.

Due to the prominent advantages, such as low cost, good scalability, spatiotemporal coverage, the mobile crowdsensing can enable attractive sensing applications in various domains [1], such as healthcare [2], transportation [3], environmental monitoring [4], noise monitoring [5], activity monitoring [6], and social network [7].

In the mobile crowdsensing systems, the employed participants would spend their time and consume battery, memory, power, and data traffic [29] for completing the sensing tasks. In addition, participants may suffer privacy breach when they share their sensing data with location tags, interests

or identities. Therefore, the rational participants will not participate in the mobile crowdsensing, unless their resource consumption and potential privacy breach can be sufficiently compensated. The incentive mechanisms are crucial for mobile crowdsensing systems to attract rational participants and achieve good service quality.

Improving the quantity and quality of participants is still the pivotal problem, since the mobile crowdsensing systems are largely dependent on the quantity and quality of participants.

In reality, the participants are not sufficient in many mobile crowdsensing systems. According to the data of the fourth quarter in 2016 from Analysis [36], only 6.02% and 3.83% of all registered users can provide the real-time sensing data for the traffic condition in Tencent map and Tianyi navigation, respectively. Many researchers focused on developing incentive mechanisms to entice participants to participate in mobile crowdsensing [10], [11], [25], but most of them assume that there are enough participants.

Moreover, the success of the mobile crowdsensing applications highly depends on whether a crowd of qualified users can be recruited to perform the sensing tasks. For example,

there is a mobile crowdsensing application for monitoring the urban air pollution level. The sensing platform requires the pollution readings for multiple specific locations in the city. The quality of sensing data depends on the performance of sensors embedded in the smartphones and users' manual effort (e.g., taking the smartphone out of its pocket to collect the data, moving close to the specific locations). To improve the accuracy of the air pollution measurement, the platform intends to assign the tasks and provide payments to the users who can provide a high quality of sensing. However, the quality of users is unknown by the platform in advance. Thus, it is necessary for the platform to develop an efficient method to evaluate the quality of users.

Inspired by the influence diffusion in social networks, we extend the mobile crowdsensing systems to the social networks in order to lever the celebrity effect, and select the users with high influence to diffuse sensing tasks in the social network. In reality, the celebrities usually have shown significant influence in online social network. In the "Digital Death" campaign [14] launched December 1, 2010 for World AIDS Day, the stars sacrifice their digital lives on Twitter and Facebook until their fans donate one million dollars to buy their lives back. Finally, the million dollar donation goal was reached in six days. In Kickstarter crowdsourcing platform [26], the American musician Amanda Palmer launched a crowdsourcing project for the new CD and concert plan with target 0.1 million dollars. She got more than 1.19 million dollars ultimately.

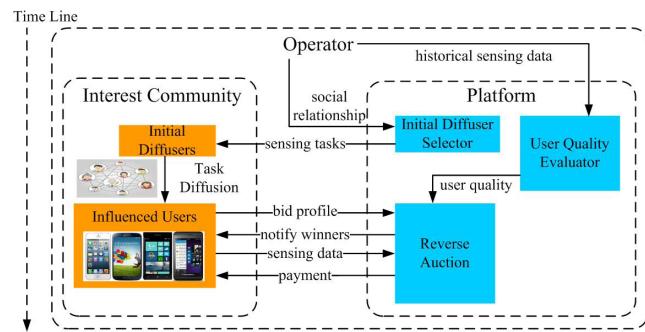


FIGURE 1. Social mobile crowdsensing architecture.

As an integrated solution, we propose a novel social mobile crowdsensing architecture to improve both participant quantity and sensing quality for mobile crowdsensing system. We extend the mobile crowdsensing systems to the social networks, and consider the quality of users when the platform selects winners. Different from most reverse auction based mobile crowdsensing systems, our social mobile crowdsensing architecture consists of three modules: initial diffuser selector, user quality evaluator, and reverse auction. We consider that the mobile crowdsensing is launched in a special interest community. As illustrated by Figure 1, the initial diffuser selector first selects a set of initial diffusers according to the social relationship in the interest community. Then the initial diffusers diffuse the sensing tasks in the

interest community. The influenced users can participate in mobile crowdsensing through the reverse auction. The user quality evaluator calculates the quality of each bidder based on the historical sensing data. Then the platform selects a set of winners according to the bid profile and the user quality, and notifies winners of the determination. The winners perform the sensing tasks and send data back to the platform. Finally, each winner obtains the payment, which is determined by the platform.

The problem of designing incentive mechanisms for above social mobile crowdsensing architecture is very challenging. First, different interest communities may show different characteristics of social connections, resulting in the diffusion processes. Thus, the initial diffuser selector should be designed from a high perspective to adapt the different diffusion models. Second, since the reverse auction makes the decision based on the user quality, the user quality evaluator should be lightweight enough in order to make the quick responses to the bidders once they submit the bids. Third, a comprehensive quality evaluation based on multiple indicators is expected since there is no ground truth in mobile crowdsensing scenario in practice. Moreover, the users may take a strategic behavior by submitting dishonest cost to maximize its utility.

The main contributions of this paper are as follows:

- To the best of our knowledge, this is the first work to give a comprehensive solution from the perspective of crowdsensing architecture design to improve both the quantity and quality of participants simultaneously.
- We propose an initial diffuser selection algorithm with the ability of accommodating the two most fashionable and widely studied diffusion models.
- We present a lightweight, multi-metric comprehensive and parameter-free quality evaluation method based on *Rank Sum Ratio (RSR)*.
- We design an incentive mechanism for our social mobile corwsening architecture to optimize the new criterion: total *Unit Quality Cost*, which takes both social cost and user quality into consideration. We show that the designed incentive mechanism satisfy desirable properties of computational efficiency, individual rationality, truthfulness, and guaranteed approximation.

The rest of the paper is organized as follows. Section II formulates the system model and diffusion models, and lists the desirable properties of incentive mechanism. Section III describes the detailed design of our incentive mechanism. The theoretical analysis of our incentive mechanism is presented in Section IV. Performance evaluation is presented in Section V. We review the state-of-art research in Section VI, and conclude this paper in Section VII.

II. SYSTEM MODEL AND DESIRABLE PROPERTIES

We consider that the mobile crowdsensing platform is operated by a social network site. The platform can know the social relationship of users from the operator. This assumption is reasonable since many social network sites operate

TABLE 1. Frequently used notations.

Notation	Description
I	set of users in the interest community
λ	number of users in the interest community
D, γ	set of initial diffusers, maximum number of initial diffusers
T, T_i, t_j, m	set of tasks, task subset of user i , task t_j , number of tasks
W, w_j	task threshold profile, task threshold of task t_j
$U(D), n$	set of influenced users, number of influenced users
b_i, c_i	claimed cost and real cost of user i
B, B_i	bid profile, bid of user i
q, q_i	quality profile, quality of user i
S	winner set
p, p_i	payment profile, payment to user i
u_i	utility of user i
σ, σ_v	influence threshold profile, influence threshold of user v
ω_{uv}, ρ_{uv}	influence and influence probability from user u to user v
$N(v)$	neighbor set of user v
$\sigma(D), \sigma_u(D)$	expected number of influenced users, marginal value of u
F^j	historical sensing data vector of task t_j for all users
η	number of indicators
$avg_j, mid_j, trim_j$	mean value, median value and trimmed mean value of any task t_j
$F_{avg}^j, F_{mid}^j, F_{trim}^j$	indicator vector of mean value, median and trimmed mean value of task t_j
$Rank_{ik}^j$	rank of influenced user i for indicator k and task t_j

mobile crowdsensing systems, such as Translate Community [37] operated by Google+, QQ-Crowd [38] operated by QQ, Crowdtesting [39] and Baidu Baike [40] operated by Baidu. Crowdsensing is a low-cost and efficient way to collect the data for improving the service of social network sites. We list the Frequently used notations in Table 1.

A. SYSTEM MODEL

The platform first chooses a special interest community in the social network according to the task types, such as healthcare, transportation, environmental, noise monitoring, and activity monitoring. We denote I as the set of users in the interest community. Without loss of generality, we consider that there are λ users in the interest community.

The initial diffuser selector selects a set of initial diffusers $D \subset I$ according to the social relations of the interest community from the operator. To incentive the task diffusion, each initial diffuser can obtain a fixed reward. Since the total reward is limited, the platform can only select a small proportion of all users in the interest community as the initial diffusers. Assume that the maximum number of initial diffusers can be selected is γ , $\gamma \ll \lambda$.

Then the platform publicizes a set of m sensing tasks $T = \{t_1, t_2, \dots, t_m\}$ and the corresponding task threshold $W = (w_1, w_2, \dots, w_m)$ to the initial diffusers, where W represents the required number of users to perform every task. Then the initial diffusers diffuse the sensing tasks in the interest community. Given the task diffusion model (will be presented in Section II-B), a set of users will be influenced by the initial diffusers, and can participate in mobile crowdsensing

through the reverse auction. Assume that a set of influenced users $U(D) = \{1, 2, \dots, n\}$ are interested in performing the sensing tasks.

Each influenced user $i \in U(D)$ submits a bid $B_i = (T_i, b_i)$, where T_i is a subset of T . b_i is the claimed cost, which is the bidding price that influenced user i wants to charge for performing T_i . The real cost c_i is only known by influenced user i , which means that the influenced user i may declare a cost b_i that is different from c_i to maximize its utility.

There is a user quality evaluator in the platform. Given the influenced user set $U(D)$ and their historical sensing data from the operator, the user quality evaluator calculates the quality of each influenced user. For each influenced user $i \in U(D)$, the user quality evaluator outputs the user quality q_i .

Given the task set T , the bid profile $B = (B_1, B_2, \dots, B_n)$, and the user quality profile $q = (q_1, q_2, \dots, q_n)$, the platform selects a subset of influenced users $S \subseteq U(D)$, and notifies winners of the determination. The winners perform the sensing tasks and send data back to the platform. Each influenced user i is paid p_i , which is computed by the platform. We denote p as the payment profile for all influenced users.

We define the utility of user i as the difference between the payment and its real cost:

$$u_i = p_i - c_i \quad (1)$$

Specifically, the utility of the losers would be zero because they are paid nothing in our designed mechanisms and there is no cost for performing tasks.

We define the *Unit Quality Cost* of any influenced user i as $\frac{c_i}{q_i}$. The objective of the incentive mechanism is to select a winner set S to complete all the tasks such that the total *Unit Quality Cost* of all winners is minimized. We refer this problem as the *Unit Quality Cost Optimization (UQCO)* problem, which can be formulated as follows:

$$\min \sum_{i \in S} \left(\frac{c_i}{q_i} \right) \quad (2)$$

$$\text{s.t. } T \subseteq \bigcup_{i \in S} T_i \quad (3)$$

In order to prevent the monopoly, we assume that all tasks still can be completed if any influenced user does not participate in the auction. This assumption is reasonable for crowdsourcing systems as made in [10], [11]. If a task can only be completed by a specific influenced user, the platform can simply remove it from T .

Remark: Although the real cost c_i is only known by user i , we will prove that claiming a false cost b_i cannot help increase the utility of user i in our designed mechanisms. Thus we still use b_i when we attempt to minimize the total *Unit Quality Cost* in the mechanisms designed below.

B. DIFFUSION MODEL

We consider both *Linear Thresholds(LT)* Model and *Independent Cascade(IC)* Model, which are two of the most basic and widely-studied diffusion models [19].

1) LT MODEL

It has the property of influence accumulation, which means that the influence from all neighbors can be accumulated, and the user can be influenced if the accumulated influence exceeds a fixed value. Each user $v \in I$ is associated with an influence threshold α_v , which indicates the latent tendency of user v to participate in the mobile crowdsensing. Let $\mathcal{D}(\alpha_1, \alpha_2, \dots, \alpha_\lambda)$ be the influence threshold profile. The influence thresholds can be evaluated through the historical participation level of users. The influence from any user u to user v , $u \neq v$, is denoted as $\omega_{uv} \leq 1$, and satisfies $\sum_{u \in N(v)} \omega_{uv} \leq 1$ for each user v , where $N(v)$ is the neighbor set of v . Any user $v \in I$ will be influenced when the total influence from the social neighbors of user v exceed his influence threshold α_v , i.e. $\sum_{u \in N(v), u \in A} \omega_{uv} > \alpha_v$, where A is the set of all influenced users.

2) IC MODEL

In this model, the user only has a single chance to influence its neighbors. After that, he/she cannot make any further attempts to influence the same social neighbors. Thus the influence from any user u to v is not cumulative, and the successful diffusion depends on the user, who is diffusing task to the neighbor currently, with probability of $\gamma_{uv} \in [0, 1]$.

We consider the *progressive* case, where any influenced user would never switch from being influenced to being uninfluenced. When the any user is influenced, he will diffuse the sensing tasks to his social neighbors. The task diffusion terminates when no users can be influenced.

The objective of *initial diffuser selection* is selecting γ users from interest community I to maximize the number of influence users $U(D)$. This *Influence Maximization* problem can be formulated as follows:

$$\max |U(D)| \quad (4)$$

$$\text{s.t. } |D| \leq \gamma \quad (5)$$

C. DESIRABLE PROPERTIES

Our objective is to design an incentive mechanism satisfying the following desirable properties:

- **Computational efficiency:** An incentive mechanism is computationally efficient if the outcome can be computed in polynomial time.
- **Individual Rationality:** Each influenced user will have a non-negative utility when bidding its true cost, i.e., $u_i \geq 0, \forall i \in U$.
- **Truthfulness:** An incentive mechanism is truthful if no influenced user can improve its utility by submitting a cost deviating from his real cost, no matter what others submit. In other words, reporting the real cost is a dominant strategy for all influenced users.
- **Unit Quality Cost Optimization:** The objective function is minimizing the total *Unit Quality Cost*. We attempt to find optimal solution or approximation

algorithm with low approximation ratio when there is no optimal solution computed in polynomial time. For the latter, the approximation ratio, $O(g(n))$, is the ratio between approximation solution and the optimal solution.

The importance of the first two properties is obvious, because they together assure the feasibility of the incentive mechanism. The last two properties are indispensable for guaranteeing the compatibility and performance. The truthful incentive mechanism can eliminate the fear of market manipulation and the overhead of strategizing over others for the influenced users.

III. INCENTIVE MECHANISM DESIGN

In this section, we present the detailed design of our incentive mechanism *DQA* consisting of *Initial Diffuser Selection*, *User Quality Evaluation*, and *Reverse Auction*.

A. INITIAL DIFFUSER SELECTION

The intuitive method is that selecting the users with high centrality [45] in the interest community as the initial diffusers. However, the centrality method does not consider the specific diffusion models.

First of all, we attempt to find an optimal algorithm for the *Influence Maximization* problem presented in (4) ~ (5). Unfortunately, as the following theorem shows, the problem is NP-hard.

Theorem 1 ([19], integration of Theorem 2.4 and Theorem 2.7): The Influence Maximization problem is NP-hard for the both LT model and IC model.

Since the *Influence Maximization* problem is NP-hard, we turn our attention to develop an approximation algorithm. A straightforward method to select the initial diffusers is selecting the user greedily with maximum degrees in the interest community. However, this method may not efficient because it cannot guarantee that the users with maximum degrees have high influence to their neighbors. Thus, we should select the initial diffusers based on the influence.

In general, the relationship between two social neighbors is closer if they share more common social neighbors. We use the *Jaccard similarity* [31] of neighbors between two users to measure the influence probability in the *IC* model:

$$\gamma_{uv} = \frac{|N(u) \cap N(v)|}{|N(u) \cup N(v)|} \quad (6)$$

For the *LT* model, the influence between two users is:

$$\omega_{uv} = \frac{|N(u) \cap N(v)|}{|N(u) \cup N(v)| \times |N(v)|} \quad (7)$$

Given any user set D , let $\sigma(D)$ be the expected number of influenced users, and let $\sigma(\emptyset) = 0$. We define the marginal value of any user u as $\sigma_u(D) = \sigma(D \cup \{u\}) - \sigma(D)$, which is the expected increase number of influenced users when u is selected as the initial diffuser.

Illustrated in Algorithm 1, *Initial Diffuser Selection* applies the greedy hill-climbing [35] to select the user with the

Algorithm 1 Initial Diffuser Selection

```

Input user set  $I$ , maximum number of initial diffusers
 $\gamma$ , influence threshold profile  $\omega$ 
Output initial diffuser set  $D$ 
1  $D \leftarrow \emptyset$ ;  $\omega' \leftarrow 0$ ;  $\gamma' \leftarrow \gamma$ ;  $A \leftarrow \emptyset$ ;  $A_{old} \leftarrow \emptyset$ 
2 while  $\gamma' > 0$  do
3    $\omega' \leftarrow \arg \max_{\omega \in I} D\sigma_{\omega}(D)$ ;
4    $A_{old} \leftarrow A_{old} \cup \{\omega'\}$ ;  $A_{new} \leftarrow \emptyset$ ;
5    $D \leftarrow D \cup \{\omega'\}$ ;  $\gamma' \leftarrow \gamma' - 1$ ;
6   for each  $\omega'' \in A_{old}$  do
7     for each  $\omega \in N(\omega'')$  do
8       if  $LT$  then  $\omega'_{\omega} \leftarrow \omega'_{\omega} + \omega_{\omega''\omega}$ ;
9         if  $\omega'_{\omega} \geq \omega_{\omega}$  then  $A_{new} \leftarrow A_{new} \cup \{\omega\}$ ;
10        end if
11       if  $IC$  then  $\omega$  is influenced with probability
12          $\tau_{\omega\omega''}$ ;
13         if  $\omega$  is influenced then
14            $A_{new} \leftarrow A_{new} \cup \{\omega\}$ ;
15         end if
16       end for
17     end for
18    $A \leftarrow A \cup A_{old} \cup A_{new}$ ;
19    $A_{old} \leftarrow A_{new}$ ;
20 end while

```

maximum marginal value iteratively until γ initial diffusers are selected. Considering the new influenced user set of the last iteration is A_{old} , then for the LT model, we have

$$\sigma_{\omega}(D) = |\{\omega \in N(\omega'') \cup N(\omega) \setminus A, \omega'' \in A_{old} \cup \{\omega\}, \omega'_{\omega} + \omega_{\omega''\omega} \geq \omega_{\omega}\}| \quad (8)$$

where ω'_{ω} is the current influence of user ω from its neighbors.

For the IC model, we have

$$\sigma_{\omega}(D) = \sum_{\omega \in N(\omega'') \cup N(\omega) \setminus A, \omega'' \in A_{old} \cup \{\omega\}} \tau_{\omega''\omega} \quad (9)$$

After selecting any user ω' into initial diffuser set, the influenced user set will be updated. For each $\omega'' \in A_{old}$ in LT model, the current influence of its uninfluenced neighbors are updated, and the neighbors will be added to the new influenced user set A_{new} of current iteration if their current influence exceed the influence thresholds. For the IC model, each uninfluenced neighbor $\omega \in N(\omega'') \setminus A$ is influenced with probability $\tau_{\omega\omega''}$. Finally, both A_{old} and A_{new} are merged into A at the end of each iteration.

Before analyzing the approximation of *Initial Diffuser Selection*, we give the following three lemmas first.

Lemma 1: The influence probability defined in (6) is an instance of the IC model, and the influence defined in (7) is an instance of the LT model.

Proof: For the IC model, there is $\tau_{\omega\omega''} \in [0, 1]$ according to (6); For the LT model, it is sufficient to prove that $\sum_{\omega \in N(\omega)} \omega_{\omega\omega} \leq 1$ for each user $\omega \in I$. According to (7),

we have

$$\begin{aligned} \sum_{\omega \in N(\omega)} \omega_{\omega\omega} &= \sum_{\omega \in N(\omega)} \frac{|N(\omega) \cap N(\omega)|}{|N(\omega) \cup N(\omega)| \times |N(\omega)|} \\ &\leq \max \frac{|N(\omega) \cap N(\omega)|}{|N(\omega) \cup N(\omega)|} \leq 1 \end{aligned}$$

■

Since we have defined the instances of the LT model and IC model, respectively, the following lemma holds.

Lemma 2 ([19, integration of Theorem 2.2 and Theorem 2.5]): For an arbitrary instance of the LT model or IC model, the resulting influence $\sigma(\cdot)$ is submodular.

Moreover, $\sigma(\cdot)$ is non-negative and monotone, i.e., adding any user into D cannot decrease $\sigma(\cdot)$: $\sigma(D \cup \{\omega\}) \geq \sigma(D)$ for each user ω and set D .

Lemma 3 [34]: For a non-negative and monotone submodular function σ , let D be a set of size γ obtained by selecting elements one at a time, each time choosing an element that provides the largest marginal increase in the function value. Let D^* be a set that maximizes the value of σ over all γ -element sets. Then $\sigma(D) \geq (1 - 1/e) \cdot \sigma(D^*)$; in other words, D provides a $(1 - 1/e)$ -approximation.

The above three lemmas together prove the following lemma.

Lemma 4: Initial Diffuser Selection can approximate the optimal solution of Influence Maximization problem within a factor of $(1 - 1/e)$ for both LT model and IC model.

B. USER QUALITY EVALUATION

Essentially, many quality evaluation methods can be applied in the user quality evaluator. For example, the EM based sensing data quality evaluation [32]. However, EM may be unsuitable in auction based mobile crowdsensing systems. First, since the bidders will wait for the decision from the platform after submitting the bids, EM based algorithm is ineffective due to the high computation complexity. Further, EM is a single indicator algorithm, while the comprehensive quality evaluation based on multiple indicators is expected since there is usually no ground truth in mobile crowdsensing scenario in practice.

In this subsection, we propose a Rank Sum Ratio (RSR) based user quality evaluation method, which is a lightweight, multi-metric comprehensive and parameter-free quality evaluation method.

Once the influenced users submit the bids, the platform calculates the quality of bidders through the user quality evaluator. We consider that there are η indicators. As an example, we define the three indicators based on mean value, median and trimmed mean value, which can be determined through the historical sensing data. Let avg_j , mid_j and $trim_j$ be the mean value, median value and trimmed mean value of any task $t_j \in T$. We denote $\mathcal{F}^j = (\beta_i^j)_{n_i}$ as the historical sensing data vector of task t_j for all influenced users in $U(D)$. Let $\mathcal{F}_{avg}^j = (|\beta_i^j - avg_j|)_n$, $\mathcal{F}_{mid}^j = (|\beta_i^j - mid_j|)_n$, $\mathcal{F}_{trim}^j = (|\beta_i^j - trim_j|)_n$ be the indicator vector of mean value, median

value and trimmed mean value of any task t_j , respectively. Note that all three indicators in our example are low optimal indicators. We rank these indicators in non-increasing order. Let $Rank_{ik}^j$ be the rank of any influenced user $i \in U(D)$ for indicator k and task t_j . Specifically, let $Rank_{ik}^j = 1, k = 1, 2, \dots, \eta$, if the influenced user i didn't perform the task t_j before. Then the quality of any influenced user $i \in U(D)$ can be calculated as:

$$q_i = \frac{\sum_{j=1}^m \sum_{k=1}^\eta Rank_{ik}^j}{n \times \eta \times m} \quad (10)$$

C. REVERSE AUCTION

First of all, we attempt to find an optimal algorithm for the *UQCO* problem presented in (2) ~ (3). Unfortunately, as the following theorem shows, the *UQCO* problem is NP-hard.

Theorem 2: The UQCO problem is NP-hard.

Proof: We demonstrate that the *UQCO* belongs to NP firstly. Given an instance of *UQCO*, we can check whether the winners can perform all tasks and check whether the *Unit Quality Cost* is at most λ . This process can be end up in polynomial time.

Next, we prove the *UQCO* is NP-hard by giving a polynomial time reduction from the NP-hard *Weighted Set Multiple Cover* problem, *WSMC*.

Instance of *WSMC*(denoted by *A*): For an universe set $T = \{t_1, t_2, \dots, t_m\}$ of m elements, each t_j is associated with a positive integer \exists_j , for $j \in \{1, 2, \dots, m\}$. There is a family of sets $G = \{T_1, T_2, \dots, T_n\}$ and a positive real λ , each $T_i \subseteq T$ has its weight c'_i for $i \in \{1, \dots, n\}$. The question is whether exists a set $G' \subseteq G$ with $\sum_{T_i \in G'} c'_i \leq \lambda$, such that any element $t_j \in T$ can be covered by \exists_j times?

We consider a corresponding instance of general *UQCO*(denoted by *B*): There is an universe task set $T = \{t_1, t_2, \dots, t_m\}$ of m tasks, and each task t_j is associated with a task threshold w_j , for $j \in \{1, 2, \dots, m\}$, where w_j is a positive integer. There is a family of task sets $E = \{T_1, T_2, \dots, T_n\}$ and a positive real λ , each user $i \in U(D)$ is associated with a task set T_i and a *Unit Quality Cost* c_i/q_i for $i \in \{1, \dots, n\}$. The question is whether exists a set $E' \subseteq E$ with $\sum_{T_i \in E'} c_i/q_i \leq \lambda$, such that any task $t_j \in T$ can be performed by w_j times?

This reduction from *A* to *B* ends in polynomial time. We can simply see that x is a solution of *A* if and only if x is a solution of *B*. ■

Since the *UQCO* problem is NP-hard, it is impossible to compute the winner set with minimum total *Unit Quality Cost* in polynomial time unless P=NP. We design our reverse auction through a greedy approach. Illustrated in Algorithm 2, the reverse auction consists of winner selection phase and payment determination phase.

In the winner selection phase, the influenced users are essential sorted according to the *Effective Unit Quality Cost*. Given any uncovered task set T' , the *Effective Unit Quality Cost* of influenced user i is defined as $\frac{b_i/q_i}{|T' \cap T_i|}$. In each iteration of the winner selection phase, we select the influenced

Algorithm 2 Reverse Auction

```

Input: influenced user set  $U(D)$ , task set  $T$ , task threshold  $W$ , bid profile  $B$ , quality profile  $q$ 
Output: winner set  $S$ , payment profile  $p$ 
//Winner Selection Phase
1  $T' \leftarrow T, S \leftarrow \emptyset;$ 
2 foreach  $t_j \in T'$  do  $w'_j \leftarrow w_j;$ 
3 while  $T' \neq \emptyset$  do
4    $i \leftarrow \arg \min_{k \in U(D)/S} \frac{b_k/q_k}{|T' \cap T_k|};$ 
5    $S \leftarrow S \cup \{i\};$ 
6   for each  $t_j \in T' \cap T_i$  do
7      $w'_j \leftarrow w'_j - 1;$ 
8     if  $w'_j = 0$  then  $T' \leftarrow T' \setminus \{t_j\};$ 
9   end for
10 end while
//Payment Determination Phase
11 foreach  $i \in U(D)$  do  $p_i \leftarrow 0;$ 
12 for each  $i \in S$  do
13    $U'(D) \leftarrow U(D)/\{i\}, T'' \leftarrow T, S' \leftarrow \emptyset;$ 
14   foreach  $t_j \in T''$  do  $w'_j \leftarrow w_j;$ 
15   while  $T'' \neq \emptyset$  do
16      $i_k \leftarrow \arg \min_{k \in U'(D)/S'} \frac{b_k/q_k}{|T'' \cap T_k|};$ 
17      $p_i \leftarrow \max\{p_i, \frac{|T'' \cap T_i| \times q_i}{|T'' \cap T_{i_k}| \times q_{i_k}} b_{i_k}\};$ 
18      $S' \leftarrow S' \cup \{i_k\};$ 
19     for each  $t_j \in T'' \cap T_{i_k}$  do
20        $w'_j \leftarrow w'_j - 1;$ 
21       if  $w'_j = 0$  then  $T'' \leftarrow T'' \setminus \{t_j\};$ 
22     end for
23   end while
24 end for

```

user with minimum *Effective Unit Quality Cost* over the unselected user set $U(D) \setminus S$ as the winner until the winners together can perform each task $t_j \in T$ by w_j times.

In payment determination phase, for each winner $i \in S$, we execute the winner selection phase over $U(D) \setminus \{i\}$, and the winner set is denoted as S' . We compute the maximum price that the influenced user i can be selected instead of each influenced user in S' . We will prove that this price is a critical payment for influenced user i later.

IV. MECHANISM ANALYSIS

In this section, we present the theoretical analysis, demonstrating that our incentive mechanism *DQA* can achieve the desired properties of computational efficiency, individual rationality, truthfulness, and unit quality cost optimization.

Lemma 5: DQA is computationally efficient.

Proof: It suffices to prove that all *initial diffuser selection*(Algorithm 1), *user quality evaluation*, and *reverse auction*(Algorithm 2) are computationally efficient.

In algorithm 1, selecting the user with the maximum marginal value (line 3) takes $O(\lambda^3)$ since each diffusion takes $O(\lambda^2)$, and any user in the interest community can be

selected as the diffuser. Updating the new influenced user set (line 6-17) takes $O(\lambda^2)$. Therefore, the running time of *initial diffuser selection* is bounded by $O(\gamma \cdot \lambda^3)$ since we select at most γ initial diffusers.

For *user quality evaluation*, the time complexity is dominated by ranking the indicator vectors for all influenced users and tasks. Calculating each indicator vector ($Rank_{ik}^j$ in (10)) for all n influenced users for any task takes $O(n)$. Thus, ranking each indicator vector takes $O(n \log n)$. Since there are η indicator vectors and m tasks, the time complexity of ranking all indicator vectors for m tasks is $O(\eta mn \log n)$.

In algorithm 2, Finding the influenced user with minimum with minimum *Effective Unit Quality Cost* takes $O(mn)$, where computing the value of $|T' \cap T_k|$ takes $O(m)$. Hence, the while-loop (line 2-9) takes $O(mn^2)$. In each iteration of the for-loop (line 11-22), a process similar to line 2-9 is executed. Hence the time complexity of the whole auction is dominated by this for-loop, which is bounded by $O(mn^3)$. ■

Lemma 6: DQA is individually rational.

Proof: Let i_k be influenced user i 's replacement which appears in the i th place in the sorting over $U(D) \setminus \{i\}$. Since i_k would not be at i th place if i is considered, we have $\frac{b_i/q_i}{|T' \cap T_i|} \leq \frac{b_{i_k}/q_{i_k}}{|T' \cap T_{i_k}|}$. Hence $b_i \leq \frac{|T' \cap T_i| \times q_i}{|T' \cap T_{i_k}| \times q_{i_k}} b_{i_k} = \frac{|T'' \cap T_i| \times q_i}{|T'' \cap T_{i_k}| \times q_{i_k}} b_{i_k}$, where the equality relies on the observation that $T' = T''$ for every $k \leq i$, which is due to the fact that $S = S'$ for every $k \leq i$. This is sufficient to guarantee $b_i \leq \max_{k \in U(D) \setminus S'} \frac{|T'' \cap T_i| \times q_i}{|T'' \cap T_{i_k}| \times q_{i_k}} b_{i_k} = p_i$. ■

Before analyzing the truthfulness of *DQA*, we first introduce the Myerson's Theorem [41].

Theorem 3 ([11, Theorem 2]): An auction mechanism is truthful if and only if:

- *The selection rule is monotone: if user i wins the auction by bidding b_i , it also wins by bidding $b'_i \leq b_i$;*
- *Each winner is paid the critical value: User i would not win the auction if it bids higher than this value.*

Lemma 7: DQA is truthful.

Proof: Based on Theorem 2, it suffices to prove that the selection rule of *DQA* is monotone and the payment p_i for each influenced user i is the critical value. The monotonicity of the selection rule is obvious as bidding a smaller value cannot push influenced user i backwards in the sorting.

We next show that p_i is the critical value for the influenced user i that bidding higher p_i could prevent i from winning the auction. Note $p_i = \max_{k \in \{1, 2, \dots, L\}} \frac{|T'' \cap T_i| \times q_i}{|T'' \cap T_{i_k}| \times q_{i_k}} b_{i_k}$. If the influenced user i bids $b_i > p_i$, he will be placed after L since $b_i > \frac{|T'' \cap T_i| \times q_i}{|T'' \cap T_{i_L}| \times q_{i_L}} b_{i_L}$ implies $\frac{b_i/q_i}{|T'' \cap T_i|} \geq \frac{b_{i_L}/q_{i_L}}{|T'' \cap T_{i_L}|}$. Hence, the influenced user i would not win the action because the first L influenced users have finished all mobile crowdsensing tasks. ■

To analyze the approximation of the reverse auction, we formulate the linear program relaxation of the *UQCO*

problem as the normalized primal linear program **LP**. The dual program is formulated in program **DP**.

$$\begin{aligned} \textbf{LP}: \quad & \min \sum_{i \in S} g_i x_i \\ \text{s.t.} \quad & \sum_{t_j \in T_i} x_i \geq w_j, \quad \forall t_j \in T \\ & -x_i \geq -1, \quad \forall i \in S \\ & x_i \geq 0, \quad \forall i \in S \\ \textbf{DP}: \quad & \max \sum_{t_j \in T} w_j y_j - \sum_{i \in S} z_i \\ \text{s.t.} \quad & \sum_{t_j \in T_i} y_j - z_i \leq g_i, \quad \forall i \in S \\ & y_j \geq 0, \quad \forall t_j \in T \\ & z_i \geq 0, \quad \forall i \in S \end{aligned}$$

where g_i denotes $\frac{b_i}{q_i}$.

We define any task $t_j \in T$ as alive at any iteration in winner selection phase if its task threshold is not fully satisfied. We define that task t_j is covered by T_i if $t_j \in T_i$ and t_j is alive when user i is selected. When a set T_i is picked, its *Unit Quality Cost*, g_i is ascribed to (T_i, t_j) pairs for each alive task t_j it covers, i.e. for each such pair, $\text{cost}(T_i, t_j) = g_i / |T'_i|$, where $|T'_i|$ is the number of alive elements in T_i . For each task t_j , define $\text{max-cost}(t_j) = \max_{i \in S} \{\text{cost}(T_i, t_j)\}$, and let $y_j = \max - \text{cost}(t_j) / H_m$, where $H_m = \left(1 + \frac{1}{2} + \dots + \frac{1}{m}\right)$. If a set T_i is not picked, let $z_i = 0$, and otherwise let

$$z_i = \frac{\sum_{t_j \text{ covered by } T_i} (\max - \text{cost}(t_j) - \text{cost}(T_i, t_j))}{H_m}.$$

Lemma 8: y, z is dual feasible.

Suppose T_i is not picked in the set cover. Then, by ordering elements in the reverse order in which their requirement was satisfied and the proof of approximation guarantee for the set cover problem in [42], it is easy to check that

$$\sum_{t_j \in T_i} y_j \leq \frac{1}{H_m} \left(\sum_{j=1}^{|T'_i|} \frac{g_i}{j} \right) \leq g_i$$

Next assume T_i is picked in the set cover. Then,

$$\begin{aligned} \sum_{t_j \in T_i} y_j - z_i &= \frac{1}{H_m} \left(\sum_{t_j \in T_i, \text{and not covered by } T_i} \max - \text{cost}(t_j) \right. \\ &\quad \left. + \sum_{t_j \text{ covered by } T_i} \text{cost}(T_i, t_j) \right) \end{aligned}$$

Now, by ordering the tasks covered by T_i first, and the remaining tasks in the reverse order in which their requirement was satisfied, the right hand side of inequality can be shown to be bounded by g_i . ■

Lemma 9: The Unit Quality Cost in the UQCO problem, $IP = \sum_{(T_i, t_j)} \text{cost}(T_i, t_j) = DP \cdot H_m$.

Proof: The first equality follows from the manner in which the cost of the sets picked is attributed to the

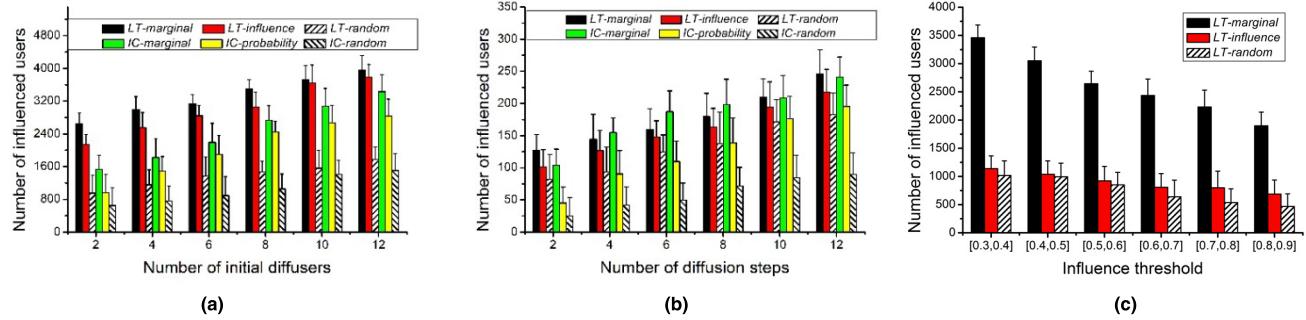


FIGURE 2. Number of influenced users: (a) impact of the number of initial users. (b) impact of the number of diffusion steps. (c) impact of influence threshold.

set-element pairs. For the second equality, notice that

$$\begin{aligned} \text{DP} \cdot H_m &= \sum_j w_j \max - \text{cost}(t_j) \\ &= \sum_{T_i} \sum_{t_j \text{ covered by } T_i} (\max - \text{cost}(t_j) - \text{cost}(T_i, t_j)) \\ &= \sum_{(T_i, t_j)} \text{cost}(T_i, t_j) = \text{IP} \end{aligned}$$

■

As a conclusion of lemma 4 to lemma 9, we have the following theorem.

Theorem 4: DQA is computationally efficient, individually rational, and truthful. Moreover, the initial diffuser selection is $(1 - 1/e)$ approximate, and the reverse auction is H_m approximate, where $H_m = \sum_{i=1}^m \frac{1}{i} \leq \ln m + 1$.

V. PERFORMANCE EVALUATION

We have conducted thorough simulations to investigate the performance of DQA based on the real word experience data. The diffusion method in DQA is based on LT model. We first measure the performance of *Initial Diffuser Selection* (termed *LT-marginal* and *IC-marginal* for *LT* model and *IC* model, respectively), and compare it with following initial diffuser selection algorithms:

- **LT-influence:** Select the user with the maximum total influence to its uninfluenced neighbors greedily.
- **IC-probability:** Select the user with the maximum total probability to its uninfluenced neighbors greedily.
- **LT-random:** Select the initial diffusers randomly under LT model.
- **IC-random:** Select the initial diffusers randomly under IC model.

Then we conduct the simulations to evaluate the cost and quality with the variation of influenced users, tasks, and the task threshold in order to reveal the impacts of the key parameters. The performance metrics include the social cost, the total unit quality cost, and the average quality of winners. To depict the user quality of solution based on the real word experience data, we define two new metrics:

Average Quality of Winners: $q = (\sum_{i \in S} q_i) / |S|$, where $q_i = 1 / (1 + d(x, y))$ and $d(x, y)$ denotes the Euclidean distance.

$d(x, y) = \sqrt{\sum_{i=1}^m (x_{it} - y_{it})^2}$, where x_{it} denotes the sensing data of task t from user i , and y_{it} describes the true value of sensing data of task t , which can be calculated by the average value of users' data.

Total Unit Quality Cost: $\mathbf{C} = \sum_{i \in S} b_i / q_i$
We compare DQA with following mechanisms:

- **Non-Quality Auction (NQA):** the reverse auction without the consideration of quality. *NQA* is a special case of Algorithm 2 by setting $q_i = 1$ for all $i \in U(D)$ essentially.
- **EM based Auction (EMA):** the mechanism evaluating each user's quality based on *EM*.

Finally, we compare the running time of *RSR* based user quality evaluation and *EM* based user quality evaluation. All of simulations were run on a Centos 7 machine with Intel Xeon CPU E5-2630 and 16 GB memory. Each measurement is averaged over 100 instances.

A. SIMULATION SETUP

In our simulations, we use real data of social network [43] from Facebook to simulate the connections between users in social network. It includes node features (profiles), circles, and ego networks with 4039 nodes and 88234 edges. As the default setting, we select 12 nodes from Facebook dataset as initial diffusers. All influenced users will take part in our mobile crowdsensing tasks. The cost of each influenced user comes from the real auction data set [44]. The default number of tasks is 50. The task threshold is uniformly over [2, 4]. The number of tasks that each influenced user submits is uniformly distributed over [3, 6]. The user quality is evaluated by the method of *RSR* or *EM*. We will vary the value of key parameters to explore the impacts of these parameters.

B. DIFFUSION PERFORMANCE

Figure 2(a) shows that the number of influenced users increases with increasing initial diffusors for all diffuser selection algorithms. We can see that *LT-marginal* and *IC-marginal* have more influenced users than *LT-influence*, *IC-probability*, *LT-random* and *IC-random*. This is because that we select the diffusers with the maximum marginal value

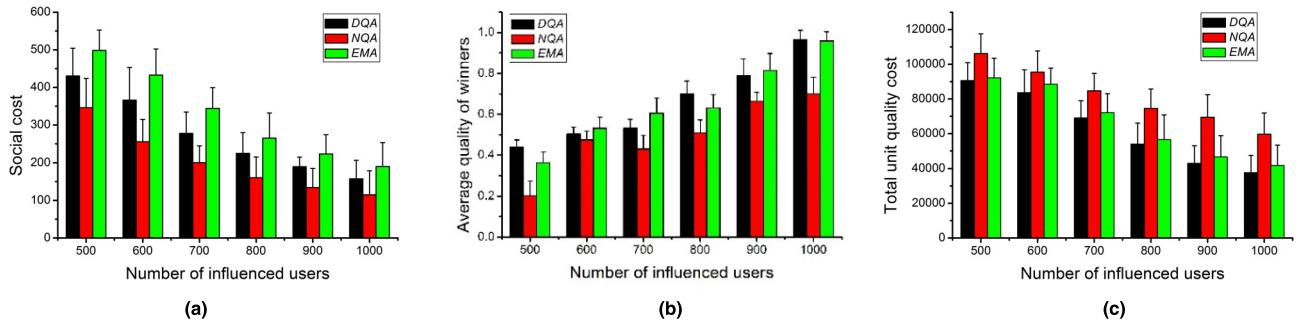


FIGURE 3. Impact of the number of influenced users (n): (a) social cost. (b) average quality of winners. (c) total unit quality cost.

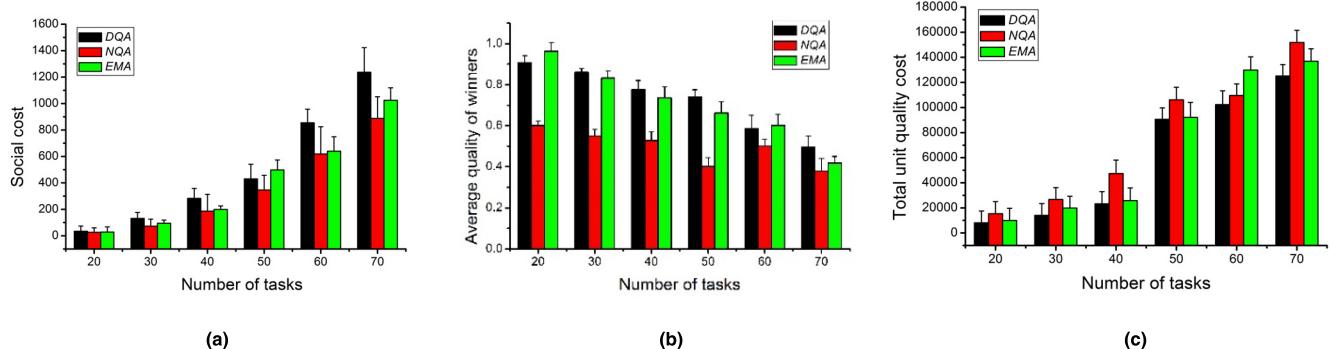


FIGURE 4. Impact of the number of tasks (m): (a) social cost. (b) average quality of winners. (c) total unit quality cost.

greedily. *LT-influence* selects the user with the maximum total influence greedily and *IC-probability* selects the user with the maximum total probability greedily. However, the user with more total influence or total probability may not have many neighbors to influence. Figure 2(b) shows that the number of influenced users increases for all diffusion model with increasing diffusion steps. The task diffusion terminates when no user can be influenced any more. This means that the number of influenced users will increase in each step until the diffusion terminates. We conduct the simulation for *LT* model with different influence threshold δ . We can see from figure 2(c) that the number of influenced users decreases when we increase the influence threshold since it would be difficult to influence the user who is with higher influence threshold in *LT* model.

C. COST AND QUALITY

We vary the number of influenced users from 500 to 1000 to investigate the impact of n in the *DQA* mechanism against the benchmarks *NQA* and *EMA*. We can see from figure 3(a) that the social cost decreases with increasing of influenced users for all three mechanisms. This is because that the platform has better choices to select the influenced users with smaller bidding price. The mechanism *NQA* has lowest social cost since it selects the influenced users with minimum cost greedily and does not consider the quality. Figure 3(b) shows that the average quality of winners increases when the number of

influenced users increases since the platform can select better users from more influenced users. We can see from figure 3(c) that *NQA* has highest total unit quality cost due to the poor quality of winners. The total unit quality cost of *DQA* is lower than that of *EMA*.

We vary the number of tasks from 20 to 70 to investigate the impact of m for all three mechanisms. We can see that the social cost increases with increasing of tasks from figure 4. This is because more users will be selected as winners for performing the tasks. Accordingly, the average quality of winners decreases with increasing number of tasks.

We vary the task threshold from [2, 2] to [2, 7] to investigate the impact of W for all three mechanisms. We can see that the social cost increases by increasing task threshold from figure 5 since the platform needs to select more winners to complete the tasks. *DQA* always shows advantage in terms of average quality of winners and total unit quality.

As a conclusion, we take *NQA* as the baseline, and give the normalized performance statistic for all above measurements in Table 2.

D. RUNNING TIME: RSR VS. EM

Figure 6 depicts the running time of *RSR* and *EM*. It can be seen that the running time increase with increasing number of tasks, number of influenced users and task threshold.

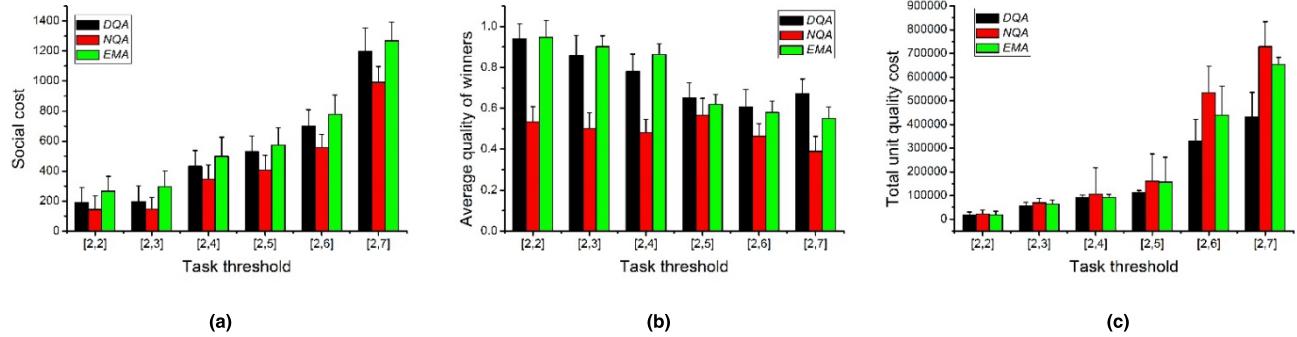


FIGURE 5. Impact of the task threshold (W): (a) social cost. (b) average quality of winners. (c) total unit quality cost.

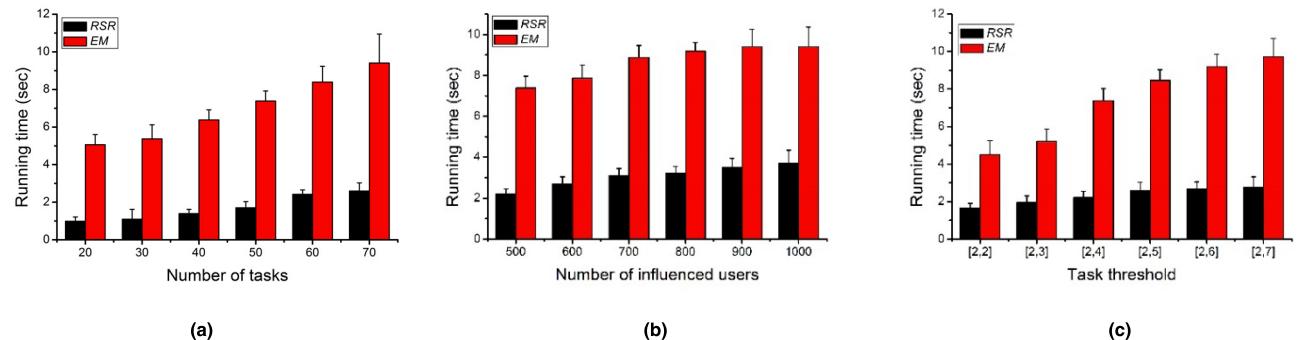


FIGURE 6. Running time of RSR and EM: (a) running time with different number of tasks. (b) running time with different number of influenced users. (c) running time with different task threshold.

TABLE 2. Normalized performance statistic.

Incentive Mechanisms	Social Cost	Average Quality of Winners	Total Unit Quality Cost
<i>NQA</i>	1	1	1
<i>DQA</i>	1.39	1.48	0.80
<i>EMA</i>	1.16	1.20	0.91

This is consistent with our time analysis in Lemma 5. The average running time of *RSR* is 2.38% of that of *EM*. The reason is that the *EM* based algorithm needs multiple iterations.

VI. RELATED WORK

In this section, we review the related work in the aspects of auction based incentive mechanisms, influence diffusion, and quality aware Incentive mechanisms.

A. AUCTIONS BASED INCENTIVE MECHANISMS

Auctions have been widely used in the crowdsensing system. The incentive mechanisms in [9]–[13], [15], [24], and [46] are all based on auction. Xu *et al.* [11] proposed truthful incentive mechanisms for the mobile crowdsensing system where the tasks are time window dependent, and the platform has strong requirement of data integrity. However, they focus on single cooperative task scenario. Yang *et al.* [12] presented two system models, the platform-centric model where the

platform provides a reward shared by participating users, and the user-centric model where users have more control over the payment they will receive. However, they only consider multiple independent task scenarios, where each task only needs one user to perform. Xu *et al.* [15] proposed a constant frugal incentive mechanism for time window coverage in mobile crowdsensing. Feng *et al.* [10] proposed a truthful auction by using the proportional share allocation rule to solve the problem of winning bid determination. However, all of above studies assume that there are enough participants who can perform the tasks. In this work, we improve the quantity and quality of users simultaneously by giving a comprehensive solution from the perspective of crowdsensing architecture design.

B. INFLUENCE DIFFUSION

There are many studies on influence maximization [20]–[22]. Kemp *et al.* [19] first formally formulated the influence maximization problem and proposed an algorithm with a ratio of $(1-1/e)$. The authors in [23] consider the product adoption maximization problem, in which they distinguished between product awareness and product adoption. Zhu *et al.* [16] studied how influence may use the initial users with minimum cost to spread its information to a certain threshold under competitors' hinder. However, there is no off-the-shelf incentive mechanism designed in the literature, which takes advantage of social network to recruit more

participants to complete the tasks in mobile crowdsensing system.

C. QUALITY AWARE INCENTIVE MECHANISMS

In recent, many data quality based incentive mechanism have been proposed [13], [17], [18], [28]. A multitask-oriented participant selection strategy was proposed in [13] to satisfy the quality-of-information (*QoI*) requirements. However, it cannot handle users' strategic behaviors. He *et al.* [27] aim to assign every sensing task to enough users in order to guarantee the quality of sensory data. This method relies on the assumption: all users have identical quality of their sensory data. In contrast, our mechanisms have the ability to handle the more general case where users may have heterogeneous data quality. Wang *et al.* [8] proposed a quality inference and parameter learning framework for workers' long-term quality between two consecutive runs based on *Linear Dynamical Systems* and *EM* algorithm. However, *EM* based algorithm is not suitable for crowdsensing system due to the high computation complexity. Chen *et al.* [30] take the service quality into online auction, and propose a truthful incentive mechanism with consideration of ex post service quality and dynamically arriving users for the mobile crowdsensing system without previous knowledge of the users. However, all of above studies only consider single indicator to evaluate the data quality. In this paper, we propose the comprehensive quality evaluation method based on multiple quality indicators to improve the accuracy of quality evaluation.

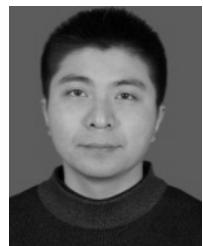
VII. CONCLUSION

In this paper, we have proposed the social mobile crowdsensing architecture, which consists of three modules: initial diffuser selector, user quality evaluator, and reverse auction to improve the quantity and quality of users simultaneously. We design an incentive mechanism for our social mobile crowdsensing architecture to optimize the new criterion, which takes both social cost and user quality into consideration. Through both rigorous theoretical analysis and extensive simulations, we demonstrate that the proposed mechanisms achieve computational efficiency, individual rationality, truthfulness, and guaranteed approximation. Moreover, the proposed incentive mechanisms show prominent advantage in total unit quality cost and running time.

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