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Reward-Aided Sensing Task Execution in Mobile Crowdsensing Enabled by Energy Harvesting

Jiejun Hu, Kun Yang*, *Senior Member* Liang Hu and Kezhi Wang, *Member IEEE*

***Abstract*—Mobile crowdsensing (MCS) is a new sensing framework that empowers normal mobile devices to participate in sensing tasks. The key challenge that degrades the performance of MCS is selfish mobile users who conserve the resources (e.g., CPU, battery and bandwidth) of their devices. Thus, we introduce energy harvesting (EH) as rewards into MCS and thus provide more possibilities to improve the quality of service (QoS) of the system. In this paper, we propose a game theoretic approach for achieving sustainable and higher-quality sensing task execution in MCS. The proposed solution is implemented as a two-stage game. The first stage of the game is the system reward game, in which the system is the leader, who allocates the task and reward, and the mobile devices are the followers who execute the tasks. The second stage of the game is called the participant decision-making game, in which we consider both the network channel condition and participant's abilities. We analyse the features of the second stage of the game and show that the game admits a Nash Equilibrium (NE). Based on the NE of the second stage of the game, the system can admit a Stackelberg Equilibrium, at which the utility is maximized. Simulation results demonstrate that the proposed mechanism can achieve better QoS and prolong the system lifetime while also providing a proper incentive mechanism for MCS.**

***Index Terms*—Task execution, energy harvest, game theory, mobile crowdsensing.**

I. Introduction

NOWADAYS smartphones have changed people's daily lives. The functions of smartphones become increasingly powerful every day, and they have rich sensory capabilities. Smartphones not only allow us to communicate with each other but also offer the possibilities of sensing the environment and collecting, processing and sharing information. These technologies empower the development of mobile crowdsensing (MCS). MCS is widely applied in our daily lives and in areas such as environment monitoring, personal healthcare, virtual reality entertainment, transportation monitoring and smart city applications [1]–[4]. It has the advantages of mobility, scalability and cost effectiveness, comparing to the traditional Internet of things. Moreover, the integration of human intelligence into the mobile sensing and computing process is also a special aspect of MCS. This means that people can decide how to and when to be a member of MCS.

Jiejun Hu and Liang Hu are with the Department of Computer Science and Technology, Jilin University, Changchun, Jilin, 130012 China e-mail: jc2015@mails.jlu.edu.cn, hul@mails.jlu.edu.cn

Kun Yang School of Computer Sciences and Electrical Engineering, University of Essex, CO4 3SQ, Colchester, U.K. and School of Communication and Information Engineering, University of Electronic Science and Technology of China.

Kezhi Wang is with Department of Computer and Information Sciences, Northumbria University, Newcastle upon Tyne, NE2, 1XE, U.K.

For a typical MCS procedure, first, the MCS server will publish the sensing task to a special area. Then, the participant recruiting procedure based on performance, reputation etc., will be triggered. All participants will begin to execute the sensing task: sensing, executing sensing data and returning the results to the server. When the sensing task is relatively easy, sensing and executing will not cause the heavy consumption of energy or other resources by the mobile devices. However, when a tough sensing task is allocated, such as multimedia data sensing and mining, participants know they have to spend more resources to accomplish the task, so some of them may choose to leave without a proper task execution plan and incentive mechanism.

Incentive mechanism is the most important issue which needs to be considered in MCS. A proper incentive mechanism can make sure the participants in MCS to donate their resource to achieve a common interest. To simulate mobile user to become a participant and remain the number of the participants, researchers have designed extensive method to provide the incentive mechanism. They adopt money, reputation and credit as reward to participants to guarantee the sensing quality [5], [6].

In our work, energy harvesting (EH) is envisioned as a promising way to address the challenge of incentive mechanism. EH can capture recyclable external energy, including solar, indoor lightening, vibrational, chemical and human motion energies [7]. The utilization of EH devices in MCS will provide new features, such as self-sustainability, coverage of sensing area and the quality of sensing result. In this paper, we adopt EH devices in MCS. The system will use the energy that can be harvested by the participants as a reward.

In the traditional MCS sensing task execution, participants only can choose to be a member and donate their own resource or choose not to be involved at all. However the traditional method maybe reduce the possibility of a potential participant by only two choices: to do or not to do. In our work, we introduce computation offloading [8], [9] into MCS sensing task execution. Thus, the participants can make different choices by analyse their resource. In addition of EH, participants' battery can be maintained and the sensing life of the system can be prolonged.

In this paper, we adopt a game theoretic solution to address the reward-aided sensing task execution in MCS, in addition to the QoS and system lifetime of MCS. Game theory focuses on the features of participant competition and interactions [7], [10], [11]. In an MCS sensing environment, any action taken by a participant affects the decisions of others in the mobile network. Thus, game theory is a natural mathematical

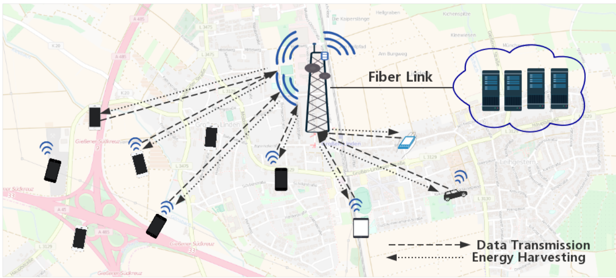

Fig. 1. Mobile Crowdsensing with Energy Harvesting Scenario

approach for studying this interaction. In this paper, the Stackelberg leadership model is a promising way to provide an incentive mechanism and solve the reward allocation problem, which enables the system and the participants to maximize their utilities at the same time [12], [13].

In this paper, we study the issue of reward-aided sensing task execution, in addition to sustainable system lifetime in MCS, and model it as a two-stage Stackelberg game. EH as a reward will also act as the incentive mechanism in MCS. This approach will reduce the energy consumption of mobile users. By giving different participants different rewards, this approach helps to control the sensing quality of the data. In summary, the contributions of this paper are as follows:

- **Reward-aided sensing task execution game formulation**: The proposed Stackelberg game consists two parts. The first stage of the game is a system reward game (SRG). In the SRG, the system that allocates the tasks and reward is the leader, and the mobile devices that execute the tasks are the followers. The second stage of the game is called a participant decision-making game(PDG); both the system and mobile devices are players in the second stage. The strategy of the system is the optimal reward, and the optimal strategy of the participants is how to execute the task.
- **Properties of the game**: The PDG in the framework ensures that the SRG has an optimal result. Because the sub-game has an NE, all the mobile devices can achieve a mutual satisfaction. As a result of the sub-game, the participants in MCS will be separated into two groups: those who offload the task and those who execute the task locally. Based on their different decisions in sensing task execution, the system will allocate the reward to different participants.
- **Reward-aided sensing task execution mechanism and main algorithms**: The proposed Stackelberg game is achieved by two main algorithms, which operate in tandem: In PDG, algorithm1 takes communication interference, computation time and energy into account and achieves the Nash equilibrium of the decision-making game. In SRG, based on the result of algorithm1, algorithm 2 can achieve the optimal reward amount and allocate the reward.

The remainder of this paper is organized as follows. In section II, we discuss the related works. The system model is introduced in section III. The Stackelberg game and reward-aided sensing task execution mechanism are presented in sections IV and V, respectively. The performance and simulation of the mechanism are analysed in section VI. In section VII, we conclude the paper.

II. Related Work

The incentive mechanism and sensing quality play crucial roles in MCS. Related works have showed different incentive mechanisms: they adopt money, reputation and credit as rewards for participants [5], [6].

In [14], two types of incentive mechanisms are introduced: a user-centric model based on the Stackelberg game and a system-centric model based on auction. In [15], the authors proposed a new crowdsensing framework, namely, social network assisted trustworthiness assurance (SONATA), which aims to maximize the crowdsensing platform utility and minimize the manipulation probability through vote-based trustworthiness analysis in a dynamic social network architecture. [16] designed an inventive mechanism for discrete crowdsensing in which each user has a uniform sensing subtask length. The objection of this work is to maximize the platform utility and achieve perfect Bayesian equilibrium. [17] studied the incentive mechanisms for a novel Mobile Crowdsensing Scheduling problem, which achieved desirable truthfulness, individual rationality and computational efficiency. However there is no work which takes energy as a reward in MCS. In our work, energy plays a significant role in MCS, because energy as a reward can guarantee the quantity of the participants, and then sustain the coverage of sensing area, all these improve the QoS in MCS.

For the sensing quality of MCS, Jin et al. [18] proposed a reverse auction approach for the incentive mechanism of MCS based on quality of information (QoI). In [19], the authors presented a framework for green mobile crowdsensing that utilized a quality-driven sensor management function to continuously select the k-best sensors for a predefined sensing task. In [20], a novel approach was proposed that uses the techniques of evolutionary algorithms to determine the optimal trade-off between data quality and cost. In our work, we adopt computation offloading as an additional option for the participants. Computation offloading make it possible to execute heavy sensing task in the cloud and return the result directly back to the server. Budgets in MCS is also an essential parameter when MSC platform maximizes the sensing quality. [21] proposed a novel task allocation framework called CrowdTasker for MCS. CrowdTasker aims to maximize the coverage quality of the sensing task under a budget constraint by greedy algorithm. [22] and [23] proposed a framework to achieve the optimal coverage quality under budget constraint.

For EH, this approach is widely applied in many scenarios in wireless sensor networks [24]–[28]. Wang et al. [29] studied joint channels and power allocation to improve the energy efficiency of user equipment by analysing the batteries of the user equipments. In [30], Mao et al. investigated a green mobile-edge computing system with energy harvesting devices and developed an effective computation offloading strategy. In [31], a tractable model was developed for analysing the performance of downlink heterogeneous cellular networks with both power-grid-connected base stations and energy harvesting small cell access points. In [32], energy harvesting has also been taken into consideration in cognitive radio sensor networks (CRSNs). It addressed a network utility maximization problem which is greatly impacted by sampling rate control and channel access schedule, under the harvested energy, channel capacity and interference constraints.

Our work is inspired by the works on the interference among the users in mobile networks and a game theoretic approach for maximizing the system utility [14], [33]. However, our work differs the above mentioned related works in the following ways: (a) we consider interference among participants in MCS to propose an efficient sensing task execution approach. (b) we adopt EH as a reward in the incentive mechanism, which prolongs the system lifetime of MCS. (c) our work faces a multi-parameter environment where the participants information is multi-dimensional.

III. System Model

We introduce the system model of MCS in this section. As shown in Fig. 1, we consider in a framework that consists of a set of participants $\mathcal{P} = \{1, 2, ..., p\}$,where participant i will be assigned a sensing task $T_i = \{B_i, D_i\}$ to be executed, which is published by the system. Here, B_i denotes the data size of the computation input data (which including the sensing data and the execution code), and D_i denotes the required CPU cycles of participant i. There is a wireless base station that allows participants to offload computations to the cloud. Participants in MCS can decide whether to execute locally or to offload the task to the cloud via the wireless network. We denote by d_i as the sensing task execution decision of participant i. Specifically, we have $d_i = 0$ if the participant will execute the sensing task locally, and $d_i = 1$ if the participant chooses to offload the task. The decision profile is $\mathfrak{d} = \{d_1, d_2, ...d_n\}$. In this scenario, EH is a special feature of the MCS participants. Hence, the sensing task execution model, EH model and network conditions in MCS will be discussed. We will focus on the efficient sensing tasks execution procedure and the energy-aided incentive mechanism in MCS.

A. Task Execution model

In MCS, there are two potential ways to execute the sensing tasks. Participants can choose either of them to maximize their utility. In this section, we introduce the sensing task execution model in MCS.

1) Local Execution Model: We consider each $i \in \mathcal{P}$ has a sensing task T_i, which is published by the system. We will discuss execution delay and energy consumption of the local execution model.

For local execution, a participant will execute the task with the local resources of the mobile device and generate the sensing result r_i with data size B_i^r, B_i^r can be larger or smaller than the sensing task size B_i based on the sensing task. The computational capacity of the participant i is denoted as F_i. The local execution delay $T_i^{l_1}$ and energy consumption $E_i^{l_1}$ can be expressed as follows:

$$T_i^{l_1} = \frac{D_i}{F_i} \tag{1}$$

$$E_i^{l_1} = \varphi D_i \tag{2}$$

where $\varphi = \mathcal{K} F_i^2$ denotes the energy consumption per CPU cycle, $\mathcal{K}$ is energy coefficient based on the structure of the chips [34]. In sensing result transmission process, the transmission delay $T_i^{l_2}$ and energy cost $E_i^{l_2}$ can be expressed as follows:

$$T_i^{l_2} = \frac{B_i^r}{R_i} \tag{3}$$

where R_i is the data transmission rate of participant i. Based on (3), we can have the energy consumption of the result transmission stage.

$$E_i^{l_2} = P_i \frac{B_i^r}{R_i} \tag{4}$$

where P_i is the transmission power of participant i. According to (1), (2), (3) and (4) we can obtain the local sensing task execution cost C_i^l as:

$$\begin{aligned} C_i^l &= w_1(T_i^{l_1} + T_i^{l_2}) + w_2(E_i^{l_1} + E_i^{l_2}) \\ &= w_1(\frac{D_i}{F_i} + \frac{B_i^r}{R_i}) + w_2(\varphi D_i + P_i \frac{B_i^r}{R_i}) \end{aligned} \tag{5}$$

where $w_1, w_2 \in (0, 1)$ are the coefficients of the execution delay and energy consumption. R_i is the data rate for participant i that we simply assume is the same to every local execution participant due to the interference can be discarded. A participant will compute the sensing cost before deciding whether to execute the sensing task locally or in the cloud. Note that execution delay and energy consumption are parameters with different scales, so we will use a normalization method to convert the parameters into a common scales.

2) Cloud Execution Model: In the cloud execution model, the sensing task will be executed in the cloud. For a participant, the cost of cloud execution includes two parts: the delay contributed by transmission in the network and execution in the cloud and the energy consumption of offloading the sensing task. The execution delay of the cloud execution model is denoted as T_i^o, which is given by

$$T_i^o = \frac{B_i}{R_i(\mathfrak{d})} + \frac{D_i}{F_i^c} \tag{6}$$

where $R_i(\mathfrak{d})$ is different from R_i in (4), because interference will happen when participants decide to offload the sensing task. And F_i^c is the computational ability of the cloud which we assume the system will offer every participant the same

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computation ability. We denoted the energy consumption in the cloud execution model as E_i^o:

$$E_i^o = P_i \cdot \frac{B_i}{R_i(\mathfrak{d})} \tag{7}$$

According to (5) and (6), we can compute the cost of the cloud execution, which is denoted as C_i^o :

$$C_i^o = w_1\left(\frac{B_i}{R_i(\mathfrak{d})} + \frac{D_i}{F_i^c}\right) + w_2 P_i \frac{B_i}{R_i(\mathfrak{d})} \tag{8}$$

B. Network Model

Due to the scenario of MCS, when a big amount of mobile devices begin to offload the sensing task to the cloud, the communication interference among the participants need to be considered about. In the mobile network, the base station can manage the communications of all mobile users, including uplink and downlink communications. The data transmission rate of participant i is a logarithmic function of SINR. SINR is denoted as $\gamma_i(\mathfrak{d})$ [33], [35]

$$\begin{aligned} R_i(\mathfrak{d}) &= f(\gamma_i(\mathfrak{d})) \\ &= f\left(\frac{P_i H_{i,b}}{\sigma^2 + \sum_{m \in \mathcal{P}, m \neq i, d_m = 1} P_m H_{m,b}}\right) \\ &= W \log_2\left(1 + \frac{P_i H_{i,b}}{\sigma^2 + \sum_{m \in \mathcal{P}, m \neq i, d_m = 1} P_m H_{m,b}}\right) \end{aligned} \tag{9}$$

where P_i and $H_{i,b}$ represent the transmission power of participant i and channel gain between the participant i and base station, respectively; σ^2 denotes the noise power level, including noise power and interference power. According to the equations above, if too many participants decide to offloading the sensing task, SINR will decrease, interference will incur and lead to low data rates, which negatively affect MCS. Thus in the offloading phrase, the interference needs to be taken into consideration.

IV. Reward-Aided Sensing Task Execution Game

In MCS, the system is interested in maximizing its utility while publishing the tasks and rewards for the participants. At the same time, the participants who own the mobile devices are both selfish and rational; hence, they also want to maximize their own utility. The participant must compute the cost of execution based on communication interference, energy consumption and battery level. If the system will give the him a reward that is not less than the cost, then he will participate in MCS. Firstly in our work, we assume that the system would like to have more participants to offload the sensing task to the cloud, due to the capacity of the cloud and the transmission delay of local execution. Thus there will be more reward that will be allocated to the offloading participants.

The proposed reward-aided sensing task execution mechanism is achieved by Stackelberg game, where the system is the leader who moves first in the game and the participants are the followers. In Stackelberg game, there are two stages:

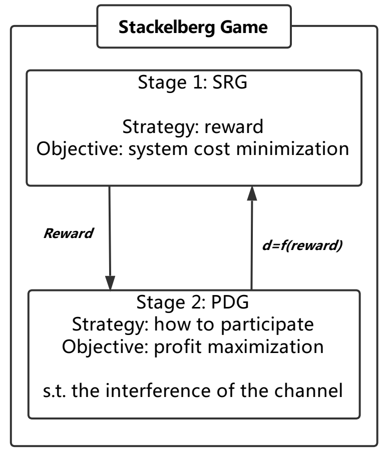

Fig. 2. Stackelberg Game

an SRG, in which the system provides reward for users who participate in computation and a PDG, in which participants can decide by themselves whether to offload the sensing task or execute it locally according to the reward from the system. In order the solve the whole Stacketlberg game, we need to solve the second stage of the game (PDG) first based on the reward from the system [36].

Before starting, there are serval important questions regarding the game, the first of which is how to choose a reasonable Utility Function (UF). After a UF has been selected, we must determine what kind of strategy a participant can choose to maximize or minimize the UF; in another words, what is the best response of a participant? Moreover, will a stable state (NE) exist for all the participants? If the system can achieve NE, will it be unique? In this section, we will address several important questions while formulating the two-stage game.

A. Utility Functions

1) Stage One of Stackelberg Game : In an SRG, the leader is the system, who makes the first move in the game, and the followers are the mobile users. The UF of the system is the cost of the system after allocating the reward to the participants, which can be formulated as

$$U_S = \sum_{i=1}^{p} E_i I_{(d_i=1)} + \sum_{i=1}^{p} E_i' I_{(d_i=0)} \tag{10}$$

where I is an indicator function, if $d_i = 1$ is true, then the indicator function is true and vice versa. In equation (10), E_i denotes as the reward for offloading participants and E_i' as the reward to local participants. $E_i' = \varepsilon E_i$ for local participants

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TABLE I
NOTATION AND DESCRIPTIONS

Notation	Description
$\mathcal{P} = \{1, 2, ...n\}$	set of participators
F_i	Participator i's computation ability
D_i	i's Required CPU circles of the sensing task
B_i	computation input data size
B_i^r	Sensing result of participant i
R_i	Uplink data rate for participator i
F^c	Computation ability of the cloud
W	Channel bandwidth
P_i	Transmission power of participant i
$H_{i,b}$	Channel gain between participant i and base station
$a_1, a_2, b_1, b_2, w_1, w_2$	Weights
$\mathfrak{d} = d_1, d_2, ..., d_n$	Decision profile of participators
ec_i	i's energy consumption
eh_i	i's harvested energy
en_i	i's new energy level after energy harvesting
ei_i	i's initial energy level
eb	i's battery ability

where ε is constant. In the first stage of Stackelberg game, the goal is to minimize the cost of the system, which implies

$$\begin{aligned} \min_{\mathfrak{d}, E_i} \quad & U_S \\ \text{s.t.} \quad & E_i \geq E_i^o \quad \forall i \in \mathcal{P} \\ & E_i' \geq E_i^{l1} + E_i^{l2} \quad \forall i \in \mathcal{P} \end{aligned} \tag{11}$$

2) Stage two of Stackelberg Game : The participant i's utility function is the profit he can make by obtaining reward from the system minus the cost of sensing task executions

$$U_i^P = \begin{cases} E_i - C_i^o & \text{if } d_i = 1 \\ E_i' - C_i^l & \text{if } d_i = 0 \end{cases} \tag{12}$$

where E_i and E_i' are different rewards he can obtain from different sensing task execution plan. In the second stage of Stackelberg game, the utility function of participant should be maximized for each participants.

$$\max_{\mathfrak{d}} U_i^P \tag{13}$$

B. Game formulation and Property

Definition 1 (Stackelberg Equilibrium). $(\mathfrak{d}^*, E_i^*)$ is a Stackelberg Equilibrium for the proposed game if it satisfied the following conditions for any value of $(\mathfrak{d}, E_i)$

$$\begin{aligned} U_S(E_i^*, \mathfrak{d}^*) &\geq U_S(E_i, \mathfrak{d}^*) \\ U_i^P(d_i^*, d_{-i}) &\geq U_i^P(d_i', d_{-i}) \end{aligned} \tag{14}$$

According to definition 1, the Stackelberg Equilibrium can be obtained as follow: in PDG, equilibrium depends on the followers' optimal response of sensing task execution plan where they will obtain the optimal strategy profile $\mathfrak{d}^*$. In SRG, system uses the optimal strategy profile of PDG to obtain the optimal reward E_i^* for the participants. Therefore, we need to analysis the PDG first, to solve the SRG.

First, we define the Best Response (BR) in the PDG. The BR is a central concept in game theory. It is a strategy that produces the maximum profit for a player in the game, given the other players' strategies.

Definition 2 (Best Response in a Decision-making Game). Participant i's strategy d_i^* is the Best Response to strategies d_{-i} of other participants, if

$$U_i^P(d_i^*, d_{-i}) > U_i^P(d_i', d_{-i}) \qquad \forall d_i \in \mathfrak{d}, d_i^* \neq d_i' \tag{15}$$

In a PDG, all the participants will act according to their BR when playing the game. Hence, the PDG will eventually reach a stable point, which we call it NE.

C. Solution of Stackelberg Game

1) Stage2 – PDG: In order to solve the Stackelberg game, we apply backward induction. First we need to solve the second stage of the game. We take the reward E_i and E_i' as given in stage 2.

Theorem 1 (Best Response strategy) According to Definition 2 and the action profile of participant i is $d_i = \{0, 1\}$, where 0 means local execution and 1 means cloud execution. Here we will discuss which action of the participant is the best response towards to other participants' actions. We assume the best response of participant i is d_i^*, according to the fixed strategy profile d_{-i} of other participants. Thus we have

$$U_i^P(d_i^*, d_{-i}) = \begin{cases} E_i - C_i^o + U_i^P(d_{-i}) & \text{if } d_i^* = 1 \\ E_i' - C_i^l + U_i^P(d_{-i}) & \text{if } d_i^* = 0 \end{cases} \tag{16}$$

in BR $d_i^* \neq d_i'$, thus we assume when $d_i^* = 1$, we obtain

$$U_i^P(1, d_{-i}) > U_i^P(0, d_{-i})$$

where we have

$$E_i - C_i^o + U_i^P(d_{-i}) \geq E_i' - C_i^l + U_i^P(d_{-i})$$
$$C_i^o - C_i^l \leq E_i - E_i'$$

on the other hand, when $d_i^* = 0$, we have

$$C_i^o - C_i^l \geq E_i - E_i' \tag{17}$$

As it shows in (17), we need to discuss the relation between C_i^l and C_i^o. According to (5) and (8), we have the left side of (17)

$$w_1(\frac{B_i}{R_i(\mathfrak{d})} + \frac{D_i}{F^c}) + w_2 P_i \frac{B_i}{R_i(\mathfrak{d})} - C_i^l$$

where we can find out the data rate when participants offload the sensing task to the cloud will strongly effect the cost of sensing task execution. Based on (9) when all the participants want to offloading the task, they will suffer a high interference in the channel. This will cause the increasing of the cost of offloading. Thus in PNG, the best response is when participant try to choose the cloud execution, which implies

$$d_i^* = \begin{cases} 1 & \text{if } C_i^o - C_i^l \leq E_i - E_i' \\ 0 & \text{otherwise} \end{cases} \tag{18}$$

To simplify the problem, we assume all the participants are homogenous, which means they are under the same channel condition and same transmission power, thus $P_1 H_{1,s} = P_2 H_{2,s} = ... = P_p H_{p,s} = k$. Based on $d_i^* = 1$ is the the best response of participants i. According to (9) and (18), we obtain

$$0 < \sum_{i=1}^{p} k I_{(d_i=1)} \leq \frac{k}{2^{\frac{w_1 B_i + w_2 B_i P_i}{(C_i^l + E_i - E_i' - w_1 \frac{D_i}{F_i^c})W}} - 1} - \sigma^2 \tag{19}$$

When $\sum_{i=1}^{p} k I_{(d_i=1)}$ is out of the range of (19), the utility function will decrease, so the participants will choose to execute locally. We can obtain the strategy profile $\mathfrak{d}^*$ of the participants

$$\sum_{i=1}^{p} I_{(d_i=1)} = \frac{1}{2^{\frac{w_1 B_i + w_2 B_i P_i}{(C_i^l + E_i - E_i' - w_1 \frac{D_i}{F_i^c})W}} - 1} - \frac{\sigma^2}{k} \tag{20}$$

2) Stage1 – SRG: From Stage2, we obtain the optimal strategy profile $\mathfrak{d}^*$. Now we will solve Stage1. According to (10) and (19), in addition with $E_i' = \varepsilon E_i$, we obtain

$$\begin{aligned} \min_{\mathfrak{d}^*, E_i} & \sum_{i=1}^{n} E_i I_{(d_i=1)} + \sum_{i=1}^{n} \varepsilon E_i I_{(d_i=0)} \\ &= (\frac{1}{2^{\frac{A_i}{B_i + C_i E_i}} - 1} - \frac{\sigma^2}{k}) E_i \\ &+ (n - (\frac{1}{2^{\frac{A_i}{B_i + C_i E_i}} - 1} - \frac{\sigma^2}{k})) \varepsilon E_i \\ &= (1-\varepsilon)(\frac{1}{2^{\frac{A_i}{B_i + C_i E_i}} - 1} - \frac{\sigma^2}{k}) E_i \\ &+ \varepsilon n E_i \end{aligned} \tag{21}$$

where

$$A_i = w_1 B_i + w_2 B_i P_i$$
$$B_i = (C_i^l - w_1 \frac{D_i}{F_i^c}) W$$
$$C_i = (1-\varepsilon) W$$

and n is the total number of the participants in MCS. In Stage1, we want to find out the smallest value of function (24).Thus, the derivative of (24) is

$$\begin{aligned} \frac{d(U_S)}{d(E_i)} &= \frac{(1-\varepsilon)(2^{\frac{A_i}{B_i + C_i E_i}} - 1)}{(2^{\frac{A_i}{B_i + C_i E_i}} - 1)^2} \\ &+ \frac{A_i C_i ln2 (1-\varepsilon) E_i 2^{\frac{A_i}{B_i + C_i E_i}} \frac{1}{(B_i + C_i E_i)^2}}{(2^{\frac{A_i}{B_i + C_i E_i}} - 1)^2} \\ &- [(1-\varepsilon)\frac{\sigma^2}{k} - \varepsilon n] \end{aligned} \tag{22}$$

where $\varepsilon \in (0,1)$,$A_i, B_i, C_i > 0$. And then we need to discuss about the second derivative of (23), namely

$$\begin{aligned} \frac{d^2(U_S)}{d(E_i)^2} &= \frac{d}{d(E_i)} [\frac{(1-\varepsilon)(2^{\frac{A_i}{B_i + C_i E_i}} - 1) +}{(2^{\frac{A_i}{B_i + C_i E_i}} - 1)^2} \\ &+ \frac{A_i C_i ln2 (1-\varepsilon) E_i 2^{\frac{A_i}{B_i + C_i E_i}} \frac{1}{(B_i + C_i E_i)^2}}{(2^{\frac{A_i}{B_i + C_i E_i}} - 1)^2}] \end{aligned} \tag{23}$$

According to (23), we can easily find out $\frac{d^2(U_S)}{d(E_i)^2}$ is positive, thus (22) is concave. Setting the first derivative of U_S to 0, we obtain the estimated E_i

$$E_i^{min} = \frac{A_i - B_i}{C_i(\frac{\sigma^2}{k} - \frac{\varepsilon n}{1-\varepsilon})} - \frac{B_i}{C_i} \tag{24}$$

According to the range of E_i, namely

$$E_i = \begin{cases} \max[E_i^o, E_i^{l1} + E_i^{l2}] & \text{if } E_i^{min} < E_i^o, (E_i^{l1} + E_i^{l2}) \\ E_i^{min} & \text{else} \end{cases} \tag{25}$$

According to (25), we can obtain the optimal reward from system to every participants individually based on how the participants execute the sensing task.

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D. Energy Harvest Model

Now we introduce the battery level update of each participant after reward allocated. The mobile devices in the MCS are equipped with EH components.

We use E_i^C, E_i, E_i^N, E_i^I and $E_i^B$to denote the energy consumption, the energy that can be harvested as reward, the new energy level, the initial energy level and battery capability of the participants, respectively. According to (2), (4), (7), we have

$$E_i^C = \begin{cases} E_i^o \\ E_i^{l_1} + E_i^{l_2} \end{cases} \tag{26}$$

According to energy aided reward in MCS, we have

$$E_i^N = \begin{cases} E_i^B & \text{if } E_i^I - E_i^C + E_i^H \geq E_i^B \\ E_i^I - E_i^C + E_i^H & \text{otherwise} \end{cases} \tag{27}$$

Equation (27) shows the new battery level of participants after energy harvesting.

V. Reward-Aided sensing task execution Mechanism

In this section, we introduce the reward-aided sensing task execution mechanism and the main algorithms. We suppose that the system publishes a sensing task that requires the mobile devices in the specific area to record a video for data mining.

A. Mechanism Design

- The system will announce the task to all the participants in the specific area, including all the parameters of the sensing task (the size of the task, required CPU, etc.) and the reward to the participants based on different sensing task execution plan;
- Based on the parameters of the sensing task, the parameters of the participants (battery level, bandwidth, data plan, and CPU), the channel in the mobile network and the reward, the participants will decide whether to execute the sensing task locally or offload it to the server;
- The system will allocate the rewards to different participants based on the sensing task execution plan. The participants will get the energy and renew their battery level;
- The cost of system is optimized and the lifetime of the system will be prolonged.

B. Main Algorithms

Based on Theorem 1, Algorithm 1 is designed to achieve optimal strategy profile in a decision-making game. In other words, after the algorithm 1 has been carried out, all the participants will be separated into two groups. In this algorithm, first the cost of execution will be calculated and the difference will be ranked in ascending order; then, based on the best response, the participants will make different decisions. Here

Algorithm 1 Participators Decision-making Game

Input: metrics of channel, task, participators' ability and reward
Output: $\mathfrak{d}^*$
Let $C_i^o[c_1^o \dots c_i^o]$, $C_i^l[c_1^l \dots c_i^l]$ and $\mathfrak{d}[d_1 \dots d_i]$ be new arrays
Let $i = 1$
for $i = 1$ to n **do**
  $C_i = C_i^o - C_i^l$
end for
Sort C_i in ascending order
Let $j = 1$
for $j = 1$ to n **do**
  if $\sum_{i=1}^{n} kI_{(d_i=1)} \leq \frac{k}{\frac{w_1 B_i + w_2 B_i P_i}{2^{(C_i^l + E_i - E_i' - w_1 \frac{D_i}{F_i^C})W} - 1}} - \sigma^2$ **then**
    $d_j = 1$
    $\mathfrak{d}^* = d_j \bigcup \mathfrak{d}$
  end if
end for

in Algorithm1, we obtain the optimal decision profile of the second stage of Stackelberg game. Algorithm 2 determines the reward that will be allocated to the participants. We adopt the result of the solution of stage1 to find the optimal reward for the system to allocate to the participants. It is based on the utility functions of the SRG.

Algorithm 2 System Reward Allocation

Input: $\mathfrak{d}$
Output: reward E_i and the new battery level E_i^N
Let $reward = 1$
for $i = 1$ to n **do**
  if $d_i \neq 0$ **then**
    $i++$
  end if
end for
$E_i = \max(\frac{A_i}{\frac{\sigma^2}{k} - \frac{\varepsilon n}{1-\varepsilon}} - \frac{B_i}{C_i}, P_i \frac{B_i}{R_i(\mathfrak{d})}, \frac{1}{\varepsilon}(\varphi D_i + P_i \frac{B_i^r}{R_i})$
for $j = 1$ to n **do**
  if $d_i = 1$ **then**
    $E_i^I - E_i^C + E_i$
  else
    $E_i^I - E_i^C + \varepsilon E_i$
  end if
end for

Here, we analyse the battery levels of all the participants to determine whether the proposed mechanism can achieve a longer system lifetime. Although system lifetime is an important parameter in MCS, there has been little work in this area. Therefore, a deeper collaborative approach for energy harvesting in MCS will be developed in the future work.

VI. Performance Evaluation

We evaluate the performance of the reward-aided sensing task execution mechanism and its algorithms by performing simulations. The simulation results are obtained using MATLAB on a computer with Intel i5 at 1.3 GHz.

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A. Simulation Setup

We simulate an MCS environment that consists of 20 participants with a sensing task with a data size of 420KB and 1000 Megacycles of required CPU. The computational capability of each participant is randomly selected from 1.0, 0.8 and 0.5 GHz. The bandwidth of the channel is set as 5.5 MHz, the transmission power is 100 mWatts, and the background noise is -100 dBm. The capability of the cloud is 100 GHz.

To represent the sensing quality, we proposed the sensing quality metric to measure the QoS of the system [37], which is denoted by ψ

$$\psi = \frac{\sum_{i=1}^{p} \sigma_1 F_i^c I_{(d_i=1)} + \sum_{i=1}^{p} \sigma_2 F_i I_{(d_i=0)}}{Expected} \tag{28}$$

where $Expected$ is the expected quality level of the MCS system; here, we set $Expected = 100$. The QoS index indicates how MCS executes the sensing task; since the cloud has more computation power for better executing the sensing task, we set $1 > \sigma_1 > \sigma_2 > 0$.

B. Performance Evaluation of the Rewarded-aided Sensing Task Execution Mechanism

The following simulation results provide an insight into the performance of the reward-aided sensing task execution mechanism. The metrics that interest us include the utilities of the system and participants, system lifetime and sensing quality, along with the effects of the numbers of participants, sensing task size and reward. The performance of the proposed mechanism is also compared with that of traditional MCS sensing task execution strategy, in which all tasks are sensed and executed locally. In addition to the local strategy, we also adopt a non-cooperative game as a new comparison [38]. In a non-cooperative game, based on equation (12) the participant's utility function, the participants will compete according to a fixed reward to maximize the utility by offloading sensing task.Thus, we set a non-cooperative algorithm and local sensing task execution as the benchmarks.

In Fig. 4, we show the utilities of system and participants in the scenario in which the MCS system consists of 20 participants and a set reward, along with a task size range from 0 KB to 5000 KB. According to the figure, when the task size is small, the values of the utilities are stable because most of the participants will execute a small task locally. As the task size increases, the participants' utility decreases, while the system's utility increases. Note that the system's and participants' utilities intersect when the task size is approximately 1250 KB, which means that in this scenario, the task size is optimal for the MCS system. Compared to the proposed mechanism, the utility of the traditional sensing task execution method is much smaller due to the low computational capability.

System lifetime is a crucial metric in MCS and can indicate how healthy an MCS is. In this paper, we adopt the reward-aided mechanism to prolong the system lifetime of MCS. We define that the system lifetime in terms of the lowest battery level of the participants. Fig. 5, Fig. 6 and Fig. 7 show the impacts of the sensing task size, reward and number of participants, respectively, on system lifetime. Fig. 5 shows the result of both mechanism, with and without energy harvesting. The proposed mechanism achieves a slower decrease and a better lifetime than the other methods. Fig. 6 shows that with the same reward, the proposed mechanism achieves a longer lifetime than the traditional one. Moreover, it shows that when the number of participants increases, the proposed mechanism becomes less competitive since the number of participants is not optimal for this special scenario. Fig. 7 shows how the number of participants affects the system lifetime. As the number of participant increases, the system life time stabilizes.

Fig. 8 shows the relation between reward and sensing quality. According to the figure, the sensing quality increases when the reward increases because more participants will offload the sensing task for execution, which achieves better quality.

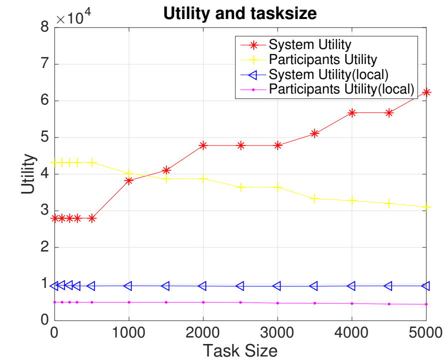

Fig. 3. System/ Participants Utility and Task Size

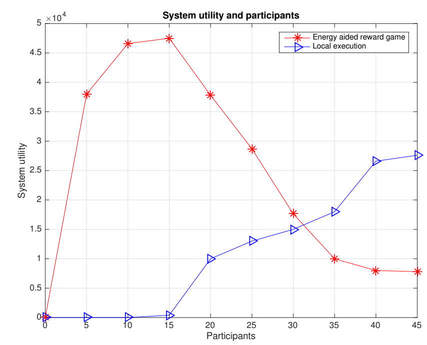

Fig. 4. System Utility and Participants

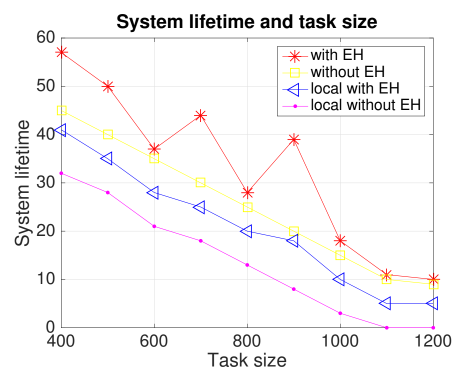

Fig. 5. System Lifetime and Task Size

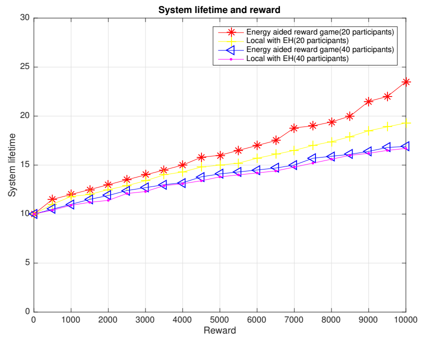

Fig. 6. System Lifetime and Reward

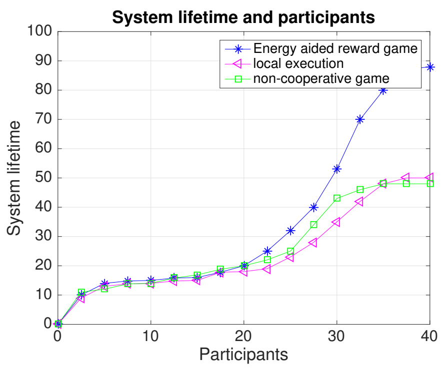

Fig. 7. System Lifetime and Participants

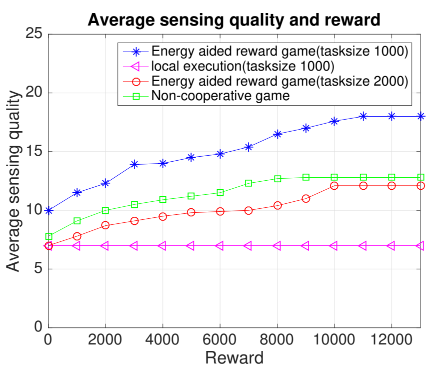

Fig. 8. Sensing Quality and Reward

However, after a certain point, as the reward increases, the sensing quality does not change. This is due to the interference of the channel, as no more participants can offload the sensing task.

VII. Conclusion

In this paper, a reward-aided sensing task execution mechanism for MCS has been proposed. The proposed mechanism aims to improve the sensing quality and prolong the system lifetime by assigning energy as a reward to the participants. The proposed mechanism adopts game theory to solve this multi-objective optimization problem. The mechanism presented in this paper considers both the network channel conditions and participants' abilities and adopts energy as the reward for the participants. Extensive simulations have demonstrated the advantages of the proposed mechanism, which yields a better QoS and a longer system lifetime for MCS.

In future work, we plan to make possible deeper collaboration between energy harvesting and MCS. We will investigate the sensing data and energy transmission in MCS to achieve a better QoS of MCS.

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Jiejun Hu received her B.E. degree in Computer Science from Jilin University in 2012. Currently she is a PhD student in Jilin University, China. Her current research areas are computer network, future network and technology, resource allocation in network, and related applications.

Kun Yang received the PhD degree from the Department of Electronic and Electrical Engineer- ing, University College London (UCL), United Kingdom. He is currently a full professor and the head of Network Convergence Laboratory (NCL) in the School of Computer Science and Electronic Engineering, University of Essex, United King- dom. Before joining in the University of Essex at 2003, he worked at UCL on several European Union Research Projects such as FAIN, MAN- TRIP, and CONTEXT. His current major research interests include heterogeneous wireless networks, fixed mobile conver- gence, and cloud computing. He has published more than 150 journal and conference papers in the above areas. He serves on the editorial boards of both IEEE and non-IEEE journals. He is a senior member of the IEEE and a fellow of the IET. Xiaohui

Liang Hu received the B.S. degree in computer systems from the Harbin Institute of Technology in 1993, and the PhD degree in computer soft- ware and theory in 1999. Currently, he is the pro- fessor and PhD supervisor of the College of Computer Science and Technology, Jilin Univer- sity, China. His main research interests include distributed systems, computer networks, commu- nications technology and information security system, etc. As a person in charge or a principal participant, he has finished more than 20 national, provincial, and ministerial level research projects of China.

Kezhi Wang received his B.E. and M.E. degrees in College of Automation from Chongqing University, P.R.China, in 2008 and 2011, respectively. He received his Ph.D. degree from the University of Warwick, U.K. in 2015. He was a senior research officer in University of Essex, U.K. Currently he is a lecturer in Department of Computer and Information Sciences, Northumbria University. His research interests include wireless communication, signal processing and mobile cloud computing.