A Survey of Incentive Techniques for Mobile Crowd Sensing

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***Abstract*—Crowd sensing (CS) is an approach to collecting many samples of a phenomena of interest by distributing the sampling across a large number of individuals. While any one individual may not provide sufficient samples, aggregating samples across many individuals provides high-quality, high-coverage measurements of the phenomena. Thus, for participatory sensing to be successful, one must motivate a large number of individuals to participate. In this work, we review a variety of incentive mechanisms that motivate people to contribute to a CS effort. We then establish a set of design constraints or minimum requirements that any incentive mechanism for CS must have. These design constrains are then used as metrics to evaluate those approaches and determine their advantages and disadvantages. We also contribute a taxonomy of CS incentive mechanisms and show how current systems fit within this taxonomy. We conclude with the identification of new types of incentive mechanisms that require further investigation.**

***Index Terms*—Crowd sensing (CS), games, incentives, reverse auction.**

TABLE I
COMMON TERMS AND ABBREVIATIONS USED IN THIS PAPER

Type of incentive	Example
Users	Private owners of the sensors
CS	Crowd sensing
QoI	Quality of information
HC	Human computing
CDS	Crowdsourcing
SC	Social computing
RADP	Reverse auction dynamic price
VPC	Virtual participation credit
RC	Recruitment
RADP-VPC-RC	Reverse auction dynamic price with virtual participation credit and recruitment algorithm
GBMC	Greedy budgeted maximum cover
BMCP	Budgeted maximum coverage problem
GIA	Greedy incentive algorithm
UDMA	Univariate model distribution algorithm
EGDE3	Third evolution step generalized differential evolution
GA	Genetic algorithm
PNP	Phone network provider
NFS	National science foundation
SMS	Short message service
VOIP	Voice over internet protocol
DTN	Delay tolerant networks
ROI	Return of investment
CENS	Center for embedded networked sensing
CRM	Community resource messenger

I. INTRODUCTION

SMART phones are devices that, in addition to allowing us to communicate with each other, are becoming powerful computation tools. These devices have the potential to sense the environment around us with a fine level of temporal and spatial granularity, and quickly transmit sensed data back to the cloud for processing and sharing. Information about noise levels and movement [24] can easily be captured using smart phones. With the addition of special purpose embedded sensors, the list may expand to include other variables such as temperature, humidity, pollution, and level of pollen in the air. All this information may be leveraged by people to better plan daily activities. For example, such information could help individuals avoid environmental conditions that represent a risk for their health [48] or change their daily commute to produce the lowest stress level [50].

CS is an appealing alternative to the traditional ways of gathering and delivering this information. In CS, sampling phenomena of interest is distributed across a large number of (often mobile) individuals rather than by any individual or set of sensors in fixed locations. These individuals carry smart phones and other sensors, which share their current location and information about their current location (e.g., temperature, pollution, and traffic). If we can distribute these samples across a sufficient number of individuals in a region, we can capture a variety of phenomena in the region without requiring fixed, expensive, difficult to maintain infrastructure.

However, the deployment of CS systems in the real world faces several challenges. Some of these include: power consumption related to the extra burden of sensing and transmitting data [59]; user's location privacy concerns, etc. [60]; and integration of sensing information from different sources types, etc. [68].

Another key challenge is motivating individuals to participate and collect data. User participation is the core of any CS system. In order to guarantee coverage and reliability, the system must always keep a minimum number of active participants [21]–[23], [35], which is not always possible due to budget constraints. This work explores a range of approaches to motivating user participation, including both monetary and nonmonetary approaches. Table I presents the acronyms used in this paper.

In this survey, we survey state-of-the-art incentive schemes for CS, as well as the sensing scenarios and network structures that motivate its application. A set of design issues are proposed, as well as a taxonomy of the current schemes. This paper

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is organized as follows. Section II presents a set of design issues or desired requirements of a CS incentive scheme. Section III presents a taxonomy of the available incentive schemes for CS. Section IV presents an evaluation of the different systems, including the advantages and disadvantages of each based on the design issues. Finally, Sections V and VI conclude this paper and provide brief directions for future work.

II. Design Issues for CS Incentive Mechanisms

After an extensive literature review, we found that most authors consider the following design characteristics as necessary conditions for the success of CS incentive mechanisms:

1) economic feasibility;
2) data quality;
3) area coverage;
4) fairness;
5) adequate number of participants;
6) adaptable to increased demands;
7) independent/human controlled.

A. Economically Feasible

For any project, budget is a critical issue. Activities like CS needs a critical mass of people to maintain both reliability and coverage. However, budget concerns may constrain these goals. Section III-B presents a review of nonmonetary incentive approaches for CS. The goal of these approaches is to appeal to specific user interest and hobbies to encourage their volunteer participation. These types of incentives involve the use of games, competition, and provide social rewards. The idea behind these types of incentives is to remove the burden associated with participating, and instead turn participation into something fun. These types of incentives allow the system to maintain a mass of participants to keep the system functional. However, its design and implementation require time and knowledge about the specific domains, and it is usually carried out by experts and experienced designers. On the other hand, monetary approaches also offer some alternatives to address this problem. A common approach is to estimate the *reservation wage*, which is defined as the lowest wage rate at which a worker would be willing to accept a particular type of job.

According to Addison *et al.* [6], the individual's reservation wage may change over time depending on a variety of factors. Taking into account the dynamic nature of this indicator, the introduction of additional components such as entertainment and competitiveness may contribute to lowering the reservation wage. Section III introduces some dynamic monetary incentives for CS that combine monetary and intrinsic motivations to make the system deployment economically feasible.

B. Data Quality

A natural question is, how can a CS incentive mechanism encourage the collection of high-quality data? One of the most common approaches utilized to address this problem is the use of reputation schemes. Generally, user reputations may be computed from past performances, the assessments of peers, or by a combination of both. Yang *et al.* [66] propose the use of this criterion to rank participants in four levels that go from very trustworthy in the top 25% to very untrustworthy in the bottom 75%–100%. On the other hand, Huang *et al.* [20] use the Gompertz function to rate the trustability level of the data provided by participants. In both cases, these reliability indicators can be linked to credit incentives in order to encourage user movement from low to top quality levels. Once computed, this indicator (e.g., trustability index) may be used to predict quality. Pham *et al.* [49] propose the use of these indicators as a criterion for data acquisition. They model the selection of participants as a multiobjective optimization problem, where quality is one of the objectives and the outcome is the best tradeoff between quality and *cost*. Reddy *et al.* [51] propose a feedback reinforcement method. They use metrics, such as timeliness capture, relevancy, coverage, and responsiveness. The feedback component continuously reinforces the improvement of these metrics by the use of monetary and social-base incentives. Finally, Liu *et al.* [36] propose an *on demand* method for data acquisition, in which each query is associated with a required quality level. The user credit reward is linked to the QoI satisfaction index of the customer. In this way, depending on the query quality level requirement, the information is directed to the group that may provide this quality level.

C. Area Coverage

Addressing the problem of area coverage in CS is a complex task for incentive mechanisms. Suppose that the variable of interest is temperature, and the goal is to estimate the temperature in a city. The logical decision would be to buy samples from users who are uniformly spread throughout the city. Some challenges include how to address the problem of the geographically unbalanced price of the samples (i.e., cheaper samples in some regions and too expensive in others), and how to address the lack of participants in some regions, and the excess of them in others. In the former case, the system buys just the cluster with the cheapest samples (i.e., poor coverage), and in the latter case, the available samples are located just in some regions of the target area.

On the other hand, the variability of the variable of interest may be different in some regions. Regions with high variability will need more samples to reconstruct the variable, whereas those with less variability will need less samples to do the same. In both cases, the challenge is in estimating the variability of regions, and then choosing the right number of participants per region to reconstruct the variable in that region.

Approaches to address these problems include the work of Reddy *et al.* [53], who propose the use of mobility profiles as part of the participant selection criteria in the recruitment process. Using a similar approach, Falaki *et al.* [18] and Shilton *et al.* [54] propose increasing the participant demographic diversity and social network affiliation. They propose leveraging the mobility patterns of different groups to increase the sensing coverage area. Kuznetsov and Paulos [30] propose the involvement of stakeholders such as students, parents, bicyclists, and homeless people. They say that each of these groups is distributed in different ways in different public spaces.

Jaimes *et al.* [21]–[23] address the imbalance of price and user location by combining the greedy budgeted maximum coverage algorithm (GBMCA) and reverse auction dynamic pricing (RADP-VPC) [35]. The result is a greedy algorithm that selects a representative subset of the users according to their location to maximize the area coverage while minimizing the cost. Finally, Mendez *et al.* [40] propose the use of density maps to assess the variability of the variable of interest in different regions and then estimate the number of participants per region.

D. Fairness

Fairness is a key factor in accomplishing goals such as retention of users, coverage, and economic feasibility. Usually, this concept is understood as equal opportunity for all participants. However, in the case of dynamic pricing models based on reverse auctions, fairness is understood as a scheme in which users with cheaper bids have a higher chance of being selected than those with higher bids. In this context (incentive models based on reverse auctions), such fairness may lead to an imbalance in geographical coverage as well as user drop out. In the former case, the participants with a lower reservation wage may be located in a particular region of the target area. In the latter case, the samples will always be acquired from those with a lower reservation wage (i.e., fairness). After several rounds of bidding without winning, most of the participants with higher bids will abandon the system. Lee and Hon [35] address this problem by the use of mechanisms such as virtual participation credit (VPC) and recruitment credit (RC). This mechanism, described in Section III-A2, avoids acquiring samples from the same users (e.g., the cheapest ones). On the other hand, Pham *et al.* [49] tackle this situation using a mechanism that not only considers the sample's price, but also its quality. Jaimes *et al.* [23] approach the same problem by means of a greedy algorithm that not only considers the sample's price, but also its location. User location and mobility patterns increase or decrease the chances of a user being chosen. Following a completely different approach, Luo and Tham [37] propose the incentive with demand fairness (IDF) method. Here, there are N participants and a service provider. Time is slotted, and in each slot, each user plays the role of a data contributor as well as a service consumer. A participant $i \in [1, \ldots, N]$ is characterized by a quadruple $< \psi_i, c_i, Q_i, q_i >$, where ψ_i corresponds to the contribution of user i in the current slot, c_i is the cost incurred by the user i to make a contribution, Q_i is the amount of service the user demands to consume in the next slot, and q_i $(q_i \leq Q_i)$ is the quota that the service provider grants to the user for the next slot. The goal is to assign an amount Q_{tot} of service quota to N users according to their characterizing quadruple. In other words, each user i receives a service quota q_i, which is proportional with both his contribution level ψ_i and his demands Q_i. Hence, this policy maximizes fairness and encourages user participation.

E. Adequate Number of Participants

Keeping a minimum number of participants to guarantee coverage and quality is a critical problem in CS. The success or failure of a CS scheme depends directly on the ability of system to hold a critical mass of participants. The remainder of this paper surveys the different types of CS incentives that aim to maintain the necessary number of participants to keep the system functional. Variables, such as frequency of sample acquisition (e.g., every hour, every day), target area size, type of phenomenon to be analyzed, variability of the variable of interest, and sensing demands can be used to determine the necessary number of participants. However, ensuring selected users continuously and actively participate to satisfy sensing requests depends entirely on the incentive mechanisms.

F. Adaptable to Increased Demands

Scalability can be defined as how well a solution to a problem will work when the size of the problem increases. From this point of view, the incentive mechanism must have the ability to maintain performance, usefulness, and usability of the CS system, regardless of expansions from local to more distributed patterns. The expansions may include the inclusion of new target areas as well as offers of new services. In order to satisfy these new requirements, the system must provide mechanisms to encourage the movement of participants from local to new regions, increase their participation, and continuously recruit new participants. The system must be flexible enough to attract new participants based on their intrinsic interests and expected rewards. In other words, it may be necessary to use methods that dynamically adapt to different participant interests according to their motivations. Jaimes *et al.* [23] address the problem of participant movement from local to new regions by a modification of the RADP-VPC [35]. Here, to encourage movement to new areas, the system sends a new offer to participants located close to the new target areas. This offer is higher than that paid to any participant previously. Other approaches, include the use of social networks, such as Micro-Blogs [19], to implement an incentive called "give and take." This incentive mechanism encourages responses to queries generated by strangers. After a careful literature review, we did not find any system that examines user profiles to dynamically offer the right type of incentive or a combination of incentives.

G. Independent/Human Controlled

An equally important design issue is the ability of the system to work autonomously in the absence of human intervention, i.e., continuing user participation in scenarios in which the user acts as a passive carrier of the sensors. Lane *et al.* [33] and Kapadia *et al.* [26] classified the grade of a user's participation as opportunistic and participatory. In the former case, users volunteer their cell phones to transparently sense the environment while they continue with their daily lives without being interrupted. They may not be aware of when or how their cell phones are remotely tasked to collect and report data. In the latter case, users are actively involved in the sensing process (e.g., taking a picture, manually activating a sensor, manually accepting or rejecting a request for samples). The emergence of hybrid systems that combine these two approaches, such as [31], have led to new characteristics like the inclusion of

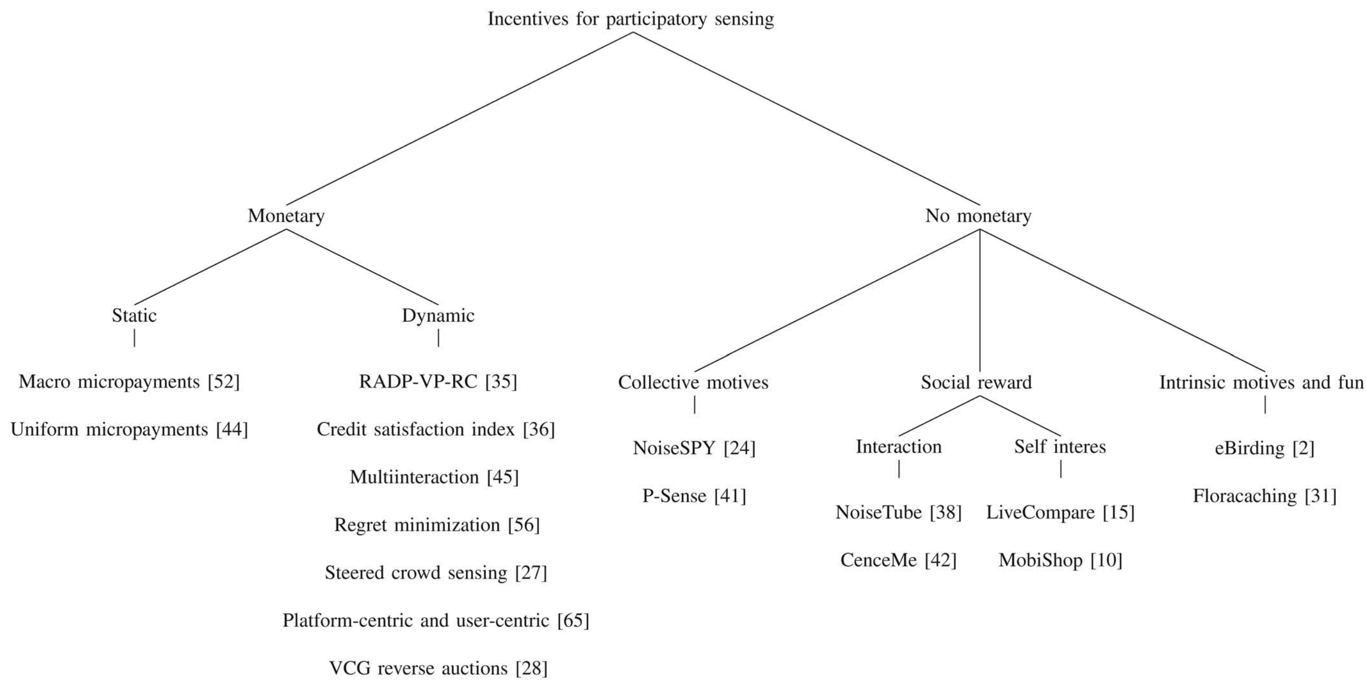

Fig. 1. Taxonomy of incentives for CS.

agents that automatically negotiate on the user's behalf. Sun and Nakata [58] propose an agent-based architecture for CS to overcome the lack of user active participation. This architecture includes five types of agents: user agents, local agents, data verification agents, event monitoring agents, and central agents. User agents provide raw data, which are processed by local and verification agents, which in turn send samples to a database. The event monitoring agent analyzes and detects database anomalies and potential hazards. Finally, the central agent is responsible for receiving and processing every query. A detailed overview of the role that systems of intelligent agents play in the design of dynamic incentive mechanisms is presented by Parkes *et al.* [47].

III. Taxonomy

CS incentives can be classified in different ways. One way is based on the order in which participants arrive to the system, namely online and offline modes. In the online mode, participants arrive one by one in a random order. Here, the assignment of a sensing task to a new participant upon its arrival is based on information about previous participants. In contrast, in the offline mode, the system knows information about all the active participants, including bids and sensing costs. Most of the incentive mechanisms described in the literature can be classified as offline techniques.

Another common way to classify incentive mechanisms for CS is based on the level of user participation (i.e., opportunistic or participatory). As there are many incentives that apply to both (i.e, opportunistic or participatory), in this work, we choose a classification based on the types of stimuli that encourage user participation. In Fig. 1, this classification approach initially identifies two large branches: monetary and nonmonetary incentives. The former can be classified as either static or dynamic. The latter are divided into the following categories: collective motives, social reward, and intrinsic motives. Social rewards are further subdivided into interaction and self-interest.

A. Monetary Incentives

When the sensing activity does not bring any immediate benefit to users, monetary rewards are a powerful motivator. They encourage participants to perform tasks that they would otherwise not perform voluntarily. The monetary reward is either static or dynamic. In the former, the amount to pay each participant is estimated in advance, and the amount may differ for each participant. In the latter, the payment depends on the reservation wage of each participant. A common approach is to combine monetary rewards with other types of incentives (e.g., intrinsic motives, social rewards) to decrease the participant's reservation wage.

1) Monetary Static Incentives: In this approach, the amount of reward is determined in advance by means of some criterion, and this amount is the same through out the whole experiment. Some examples include the first four of the five types of micropayments presented by Reddy *et al.* [52]: macro, low, medium, high, and complete micropayments. Reddy's findings showed that the method used to estimate the payment affects participation level and data quality.

On the other hand, Musthag *et al.* [44] use three types of static incentives in the form of micropayments: uniform, variable, and hidden. In the uniform scheme, a fixed amount was rewarded for completing a microtask; in the variable scheme, random amounts were assigned based on a prior distribution; and in the hidden scheme, rewards again varied, but the amount was not revealed until after the microtask was completed. Each of these incentive schemes retained around 62% of participants. However, the task completion rate was slightly higher in the variable approach with 86.92% tasks completed, followed by 86.26% for uniform, and 81.68% for hidden incentives. Their conclusions argue for the use of variable incentives (but not dynamic) over uniform and hidden. Their findings also confirm those of Reddy *et al.* [52] in that they also found that data quality is influenced by the incentive strategy.

2) Monetary Dynamic Incentives: Dynamic monetary incentives set a variable budget for each task, but the budget depends on the real-time conditions of the system. The most important works in this category are as follows.

Lee and Hon [35] present the RADP-VPC-RC, an incentive mechanism inspired by microeconomic theory and motivated by the following scenario. There are n participants spread through an area of interest. They are willing to sell their sensing data to an auctioneer, who in turn wants to acquire the m least expensive samples, within a particular time window (i.e,. rounds). The same process is repeated for k different rounds and it is carried out through a reverse auction. The first component (RADP) is a recurrent reverse auction that dynamically reduces the reservation wage of each participant (i.e., the dynamic component). Once the auctioneer buys the m cheaper samples, the winners (i.e., those who managed to sell their samples) increase their bid price by 10% expecting to increase their profits. Losers decrease it by 20% in the hope of winning in the next round. To model how drop out occurs, losers (i.e., those who could not sell their samples) evaluate their return on investment (i.e., which is based on their reservation wage and the cost of collecting data). If it is below a certain threshold, then they withdraw from the system. Otherwise, they continue participating in the next round.

In order to increase the level of participation, users who lost in the previous round $r - 1$ and continue participating are granted a VPC. Hence, losers increase their chance of winning by using their virtual bid price rather than the real bid price. Additionally, the recruitment mechanism (RC) allows the auctioneer to communicate the maximum price paid to a winner in the previous round to users who dropped out. This information allows those who drop out reevaluate their return on investment and potentially return to the system in the next auction round.

This economic model avoids two typical problems of reverse auctions: dropping out and cost explosion, making the project economically feasible by means of the combination of RADP, VPC, and RC. However, others problems such as coverage and data quality are not explicitly addressed by RADP-VPC-RC. Coverage is addressed somewhat by the use of VPC and by applying the RADP-VPC-RC simultaneously in different regions, but data quality is not addressed. Other proposals based on RADP, such as Pham *et al.* [49] and Jaimes *et al.* [23], address both coverage and data quality problems using multiobjective knapsack and budgeted maximum coverage, respectively.

Using reverse auctions as a general framework, Jaimes *et al.* [23] propose a GIA that applies the BMCP to the problem of area coverage. Given a target area A, and a set of sensors $S = u_1, u_2, \ldots, u_n$ deployed in A, GIA uses a geometrical disc model to cover the maximum area of A using a subset $S' \subset S$ of minimum cost. GIA thus aims to acquire the best located samples at a minimum cost.

Pham *et al.* [49] select the samples acquired in each round by minimizing the ratio between the price of a sample and its quality. This NP-problem is modeled as an instance of a multiobjective knapsack problem, where the constraint m is the number of samples to be acquired, and the objectives are to both maximize the quality of the acquired data and minimize costs. They solve this multiobjective optimization problem using evolutionary algorithms. Simulation results show that the proposed scheme acquires samples of high quality for 10% less money than RADP and up to 15% less than GAs.

Another representative approach is presented by Liu *et al.* [36]. This work presents a network management framework to tackle three fundamental problems: maintaining energy supply, managing QoI, and incentivizing user participation such that the PNP obtains maximum revenue. Although the solution to these three problems are related, the first two problems are outside the scope of this work. Here, we focus only on the incentivization problem.

There is a set P of users subscribed to a PNP, and a user (querier) that additionally owns a subscription to a CS plan offered by the PNP. At any time, the querier asks the PNP for contextual information about a site of interest k. The PNP in turn redirects the query to a set of N users within the proximity of k, with $N \subseteq P$. Once the query is received, the users who decided to provide data are rewarded based on the PNP's profits. Unlike the RADP-VPC-RC dynamic pricing scheme, user reward expectations are unknown in advance and must be predicted. To predict user reward expectations, this method uses recent payment history and the degree of satisfaction expressed by the user who received the recent payment.

Nan *et al.* [45] present a cross-space, multi-interaction-based dynamic incentive (CSII) mechanism for mobile CS. Here, the CS scenario has three well-defined entities, which are: 1) the requester who posts a sensing task; 2) the participants or workers; and 3) the platform which is responsible for participant selection, task price estimation, and payment mediation. When a sensing task is posted by the requester, the platform estimates the task price and suggests a budget to the requester. The requester adjusts the number of needed workers based on the budget and allows the system to select the workers that meet budgetary constraints and best match the requested sensing context for the task. The selected workers are then invited to bid for the requested sensing task, and the winners are selected based on worker bid price and reputation. Finally, both winners and losers receive a reward for participation, and winner reputations are updated based on historical data submissions. As a result, CSII achieves a dynamic budget, optimal task allocation, and high motivation to participate.

Singla and Krause [56] present an incentive mechanism based on the link between reverse auctions and the multi-arm bandit problem. In this work, the authors address two open questions in the design of CS incentive mechanisms. The first question has to do with how much to offer for a task in an online market in order to keep the CS mechanism economically feasible. The second question has to do with how to empower participants to communicate the reward they are willing to accept for a sensing task. The problem here is that the participant reservation price is private and unknown to the CS system. The proposed solution includes user participation in a reverse auction, which allows participants to express their reservation prices plus a profit. The selected winners are rewarded with an amount computed by a k-armed bandit system [56] instead of their original bid prices.

The idea behind this mechanism is to learn the reservation price curve for each participant. The prices are discretized by creating a set of k price arms, and at each time step, the mechanism picks an arm based on some optimization criterion and user feedback (i.e., accept or reject the offer). After several time steps, the mechanism may use a policy that balances exploitation (i.e., greedy policy) and exploration in order to reach a maximum average reward. The mechanism stops when the budget is exhausted.

Yan *et al.* [67] present a CS incentive mechanism in the context of sparse and DTN. Here, the nodes of a sparse wireless sensor network correspond to static sensor nodes, human relays, and sinks. The goal is to establish a virtual economic network in which the human relays make a profit by trading environmental data captured by the static nodes and themselves. These sensor data are then sent to the appropriate sinks. The scheme takes advantage of the spatial regularity of human mobility and social community patterns (e.g., community and heterogeneous centrality) to establish a data trading protocol between the mobile and opportunistic nodes.

Adeel *et al.* [7], [67] use a virtual market in the context of mobile urban sensing systems (MUSS). Here, mobile nodes (i.e., participant smart phones) conduct data trades. Profit on data trades is the difference between the selling prices of senders and receivers. This system incentivizes data forwarding between routers and base stations. Again, the elements of the network correspond to static WiFi routers, smart phones, and cellular base stations. Each mobile node can automatically switch transmission paths to a server. It can report: 1) directly through 3G and /4G networks; and 2) via the closest WIFI router; or 3) by trading the sensing data with another mobile node in order to maximize profits.

Kawajiri *et al.* [27] interpret the problem of *how to obtain a good sampling as a problem of data quality*. A good sampling of a variable of interest is a product of mobility. The goal is to incentivize participants to go to regions outside their neighborhood in order to obtain data from those far regions. The proposed mechanism starts by posting sampling tasks at different locations and corresponding rewards. The system dynamically adjusts rewards based on factors such as location visit frequency and the quality of the obtained samples. Thereby, variables such as time, location, and participants can affect the price of samples. In addition, online and real-time machine-learning-techniques are used to compute the set of participants that minimizes the task cost while maximizing the quality of data. This work is one of a few that address the problem of incentivizing user movement. However, given that the experiment took place within one building, it is difficult to generalize the results to other scenarios.

Yang *et al.* [65] define two incentive mechanisms for CS, which are: 1) the platform-centric model (PCM), where the platform has absolute control over participant rewards and 2) the user-centric model (UCM), where participants have an active role in the generation of their own rewards.

In the first case (PCM), the platform posts a sensing task and a reward R for task completion. Then, interested users submit a sensing plan containing the number of time units they are willing to provide the sensing service. The participant utility is proportional to the number of time units submitted by other participants minus its sensing cost. The platform goal is to decide the optimal value of R in order to maximize data utility. PCM is modeled as a Stackelberg game with two players the participants and the platform. The platform strategy is the reward *R*, and the user's strategy is working time. Stackelberg games have a unique equilibrium that enables the platform to maximize its utility while no user can improve his/her utility by deviating from the current strategy unilaterally. An advantage of this approach is that every participant receives a reward for participation. However, the time units submitted by every participant should be public, so that everybody can compute the payoff and decide whether or not participate.

On the other hand, the UCM incentive mechanism is a reverse auction approach. The authors show that this incentive mechanism satisfies the following desirable properties: computational efficiency, individual rationality, profitability, and truthfulness. The first three properties assure the feasibility of the incentive mechanism, whereas the last one eliminates the fear of market manipulation.

Koutsopoulos [28] introduces a CS incentive mechanism that minimizes the total compensation cost, while maintaining quality of service at a desired level. This mechanism is based on Vickrey Clark Groves (VCG) reverse auctions. Each time, a service provider receives a request for sensing, it posts the sensing task and opens a reverse auction to satisfy the request. Each interested participant submits a bid, which includes the cost per unit of sensing and participation level (i.e., sensing plan). The auctioneer then takes into account the participant sensing plan as well as the user quality score to select the winner. Once the auction is open, a Bayesian game is played among participants. They optimize the sensing cost per unit and their participation level to maximize their payoffs. The author shows that this game reaches a Bayesian Nash equilibrium. Thus, the scheme has the desirable properties of being incentive-compatible and rational for each individual.

B. *Nonmonetary Incentives*

Nonmonetary incentives allow the voluntary participation of citizens in research projects that otherwise would not be possible because of high costs of execution. Some well-known examples of such projects include Galaxy Zoo [8] (i.e., a project that involves the participation of citizens in the classification of galaxies) and eBird *et al.* [63] (i.e., a project headed by Cornell Lab of Ornithology). The advent of social networks, blogs, and smart phones have played a significant role in popularizing nonmonetery incentives. These technologies enable members of networks and communities to effectively incentivize each other to participate. Thus, our proposed classification of nonmonetary rewards has been influenced by theoretical work in social movement participation, including that of Klanermans and Stekelenburg [9], Simons *et al.* [55], and Nov *et al.* [46]. The latter surveyed 4376 volunteers and found that collective, intrinsic, and social-reward incentives were the most significant factors affecting level of participation.

We identify two subsets of social rewards incentives: interaction and self interest. In the former case, rewards come from interaction with other members of the network. Such rewards include community recognition, new friends, reputation, and community membership. In the latter case, the rewards are resources created by and shared with the community.

1) Collective Incentives: Collective incentives encourage the attainment of a common good. This is arguably the underlying philosophy of CS, to work together for a common good (i.e., a better environment, a better community, and better planet). Once the objective is reached, everybody benefits, independent of whether they participated in data collection. For instance, a public CS campaign to measure pollution levels will improve the wellness of all members of the community, not just campaign participants. According to Simon *et al.* [55], the collective good may be insufficient as a motivating force, because people may choose to wait for others to do the work instead of participate directly (i.e., "a free ride" philosophy). Thus, potential free riders may need additional incentives, such as social rewards, economic rewards, intrinsic motivation, and fun and entertainment.

Dantec *et al.* [12], [13] present a system that leverages cell phones to provide care and shelter for homeless mothers. Providers, staff, and people in need use cell phone infrastructure to improve logistics, including grocery bargain hunting that providers need to keep costs low and smart allocation of limited resources.

Mendez *et al.* [41] present P-Sense, a PS system for air pollution monitoring. The system includes sensors to measure levels of carbon dioxide, combustible gas, carbon monoxide, and air quality, as well as temperature and relative humidity. The system's goals of wellness and conservation of the environment are part of the collective interest and represent a common good.

Kanjo [24] presents NoiseSPY, a CS platform for urban noise monitoring. NoiseSPY measures and generates maps of sound levels, which can be used by citizens and urban campaigns to reduce and avoid noise contamination.

2) Social Incentives: Social motivation can play a powerful role in user participation. Millions of people join social networks each year for a variety of reasons, including: javing the opportunity to interact with other members of the community; being aware of what others are doing; building a reputation; taking self benefit from content created by the community; and using the network as a self presentation tool [11]. Han *et al.* [31] conducted a survey on features that would motivate increased user participation in CS campaigns [31]. Answers were ranked from the least motivating (1) to the most motivating (10); high ratings on features such as being able to publicly comment on observations of others (6.9 ± 2.8) and being notified when others make observations on items already observed by the participant (6.7 ± 3.2) indicate that social networking aspects of CS campaigns were highly desired. These results, along with other studies, suggest that interaction among members of the community through social networks (Facebook [29], Twitter [14], and Flickr [32], [57]) is a powerful way to motivate people to take part in CS schemes.

3) Social Interaction Incentives: The use of technologies such as social networks, blogs, SMS, email, chat, and VOIP are part of the daily communication routines of millions of people around the world. CS systems like CenceMe [42] use the concept of "sensing presence" to allow participants to share his/her status in terms of activity, disposition, habits, and surroundings (e,g., temperature, ozone levels, and noise). By sharing these characteristics, individuals with similar characteristics can more easily find and interact with each other. This network effect leads to several desirable properties, including: the number of participants can grow at a similar rate as the members of social networks; coverage and scalability are guaranteed for the same mechanism; feasibility is high due to low costs of entry (most of these communication schemes are free or inexpensive); and the system works independently and under human control.

Another CS system that uses this type of incentive is NoiseTube [39], a noise pollution monitoring application that allows participants to measure and share the levels of noise around them. This system applies the concept of social translucence [17] as a mechanism to support social interaction. NoiseTube uses visibility, awareness, and accountability to stimulate social interaction, and by extension, increase the level of participation. Participants exhibit their contributions via Elog, an environmental log, which allows participants to see maps of noise, show their contributions, and receive feedback. Furthermore, the system can be embedded into web pages and social networks, allowing participants to be aware of their participation and that of others, receive comments, and make information public for the purposes of self-promotion.

Micro-Blogs [19] propose incentives that combine social and explicit mechanisms. The social mechanism is provided through the use of social networks, which make it possible for social groups (e.g., friends in Facebook) to interact. However, to avoid confining the participation to a single social cluster, they propose the use of a pool of n free query credits for each user (i.e., the explicit mechanism). Each time a user makes a query or replies to one, his/her credits decrease or increase, respectively.

PEIR [43] also uses a model of incentives that includes interaction through social networks, careful management of privacy, and control of shared data. Users compare levels of pollution exposure via a Facebook application and make and receive comments from other users. The authors envision including mechanisms of reputation to improve the reliability of the shared information.

One advantage of these incentive mechanisms is that the CS system inherits all the advantages of social networks offer for recruitment and participation. Likewise, one can leverage the infrastructure of the social network system to maintain a mass of user participants economically. However, none of the reviewed papers mention how to pay the CS system operation costs. Followers of these incentive approaches envision CS operations costs will be charged to data providers and they in turn will offer CS data as part of a service package.

4) Intrinsic Incentives and Fun: Wiggins *et al.* [63] have demonstrated how users can be involved in active participation projects for personal fun. Typical examples of these type of incentives include games and activities, such as gardening and bird watching, where the majority of participants volunteered due to their inherent interest. An example of this type of intrinsic incentive is eBird [2]. eBird was launched by the Cornell Lab of Ornithology, in partnership with the Audubon Society. It focuses on a specific target group called birders. This project was initially based on a science-centric model of participation (i.e., Collective incentives in this taxonomy), but shifted to a *birder-centric* model. After five years, contributions went from a few thousand to around two million observations per month [46]. This example suggests that intrinsic motivations may significantly increase the level of participation when the right intrinsic incentive is used for the right target population.

Intrinsic motivation like gaming also play an important roll in the recruitment and retention of participants. Every day, people around the world spend millions of hours playing computer games. A recent report of the International Game Developer Association (Igda) [4] reveals that over 200 millions people, i.e., over 25% of all Internet users, play online games every week. Authors like Von Ahn, Law, Dabbish, and [34], [61] have pointed out the potential of *casual games*, in which the completion of tasks occurs naturally, and perhaps invisibly to the user, by playing a game. One of first works in this field was the ESP Game [62], an online game that links anonymous online individuals and has them independently tag a random online image. Once they separately suggest an identical tag, they receive points for how quickly they did so. According to Von Ahn [34], such *Human Computation Games* must be constrained by the computational problem to solve and thus requires a tradeoff between fun and practicality.

A representative incentive approach of this type is presented by Han *et al.* [31]. In order to measure the impact of using intrinsic incentives like gaming in CS projects, the CENS Lab of UCLA chose the BudBurst project [1] as a testing platform. BudBurst is an environmental CS national project that engages citizens in the collection of ecological data. CENS created a playing infrastructure, which allows participants to tag locations of observed plants; see maps and display points earned for tagging; and participate in Floracaching [3], a variant of geocaching where the goal is to find specific flowers.

C. Self-Benefits

In the self-benefits scheme, users receive immediate gratification for their participation from content created and shared by other participants [10]. By integrating each user's facet of information, the project becomes framed on a greater scale. For instance, users may submit the local price of milk, lettuce, beer, gas, etc. (perhaps by taking pictures of bar codes) and receive instant feedback about the price of the same products in nearby stores. In other words, when users make a query, they are simultaneously populating the database with updated information that may be requested by others. Stated differently, users "pay" for query results by contributing their own data. In removing monetary costs for both queriers and data providers, these systems significantly reduce the cost of running CS campaigns. LiveCompare [15] is one such system that allows users to leverage the crowd to hunt for grocery bargains. Other application are PetrolWatch [16] and MobiShop [10], which leverage the ubiquity of smart phones to share consumer gas pricing information.

The work of Luo and Tham [37], previously discussed in Section II-D, is a another good example of this category. Here, participants leverage the high-quality data of the network for their own benefit. The data they consume is proportional to their data contributions and demands. To ensure fairness, an indicator such as the Jain fairness index is used.

IV. Qualitative Comparisons of Current Systems

Table II provides a qualitative breakdown of incentives systems. We note that such qualitative comparisons are difficult because each system is designed for different scenarios, uses different approaches, and often works only for a specific sensing model. Further, some of the systems are fully operational implementations, others are pilot experiments, and others are theoretical models tested using simulations. Thus, comparing results across systems is also difficult. For example, for those systems that use social networks, it follows that the network provides coverage by default. In other cases, like Musthag *et al.* [44], Table II shows N/A on the quality field, as quality is meaningless in this context. The absence of X in Table II denotes that the corresponding design issue was not examined or the issue was examined, but the simulation performed poorly.

V. Future Research

Based on our review of the state-of-the-art in CS incentive mechanisms, we propose several research ideas and guidelines for future research.

A. Costs and Utility Functions

It is necessary to propose new, more accurate functions to estimate the cost of data acquisition. Inputs of the estimation function might include: true valuation T; data perturbation amount for location privacy purposes P; sensor quality q; elapsed time $time$ since the data request was made and the sample was taken; user reputation R; and user location L.

In addition, it is also important to propose new functions to estimate the cost the user incurs for his/her participation. This cost might be estimated as a sum of factors such as energy required to complete the task, resource consumption (e.g., time, data, and gas), and privacy concerns.

B. Schemes That Support Different Models of Sensing

In Section III-A, we reviewed four proposals with two different types of sensing models. The first model senses a region continuously in fixed time intervals (i.e., rounds). The second model senses on-demand (i.e., a user requests information about a specific place and the query is immediately directed to a group of users within the target area).

TABLE II
CLASSIFICATION OF THE TYPE OF INCENTIVES IN TERMS OF DESIGN ISSUES

Type of incentive			Incentive mechanism	Design issues						
				EcoFeasi	Quality	Coverage	Fairness	Num of users	Scalability	Control
Monetary	Static		Macro micropayments [52]	X		X	X			
			High micropayments [52]	X	X	X	X			
			Medium micropayments [52]	X	X	X	X			
			Low micropayments [52]	X	X	X	X			
			Uniform micropayments [44]	X	N/A	X	X			
			Variable micropayments [44]	X	N/A	X	X			
			Hidden micropayments [44]	X	N/A	X	X			
	Dynamic		RADPC-VPC-RC [35]			X	X	X		
			Dynamic price [49]	X	X	X	X	X		
			Manag for context-aware [36]	X		X	X			
			Bargain-based [64]		X					
			Complete micropayments [52]	X	X	X				
			Multiinteraction-based [45]	X			X			
			Regret minimization [56]	X			X			
			Selfish mule [67]	X			X			
			Self-optimizing [7], [67]	X			X			
			Steered crowd sensing [27]	X	X	X	X			
			Platform-centric and user-centric [65]	X			X			
			Vcg reverse auctions [65]	X			X			
Nonmonetary	Social rew	Interaction	CenceMe [42]		X	X	X	X	X	
			NoiseTube [39]		X	X	X	X		
			MicroBlog [19]	X	X	X	X	X		
			PIER [43]	X	X	X	X	X	X	X
		Self-inter	LiveCompare [15]		X	X	X	X		
			PetrolWatch [16]		X	X	X	X		
			MobiShop [5]		X	X	X	X		
	Collective		CRM [13]		X	X	X	X		
			PSense [41]							
			NoiseSPY [24]		X	X		X	X	X
	Intrinsic motives		eBirding [2]		X	X	X	X		
			Floracaching [31]	X	X	X	X	X		

To our knowledge, there is no incentive mechanism that simultaneously supports these two types of models. We also did not find any model that dynamically adapts the type of incentive according to the potential participant profile. We envision a personalized incentive system that automatically determines which type of incentive mechanism (e.g., monetary or nonmonetary) maximizes a specific user's contribution while still maintaining economic feasibility.

C. Type of Incentive Mechanism

The literature review found that gaming is a powerful motivator of user participation in CS. Related incentive schemes, such as lotteries and gambling, have not yet been studied in the literature.

Although several experiments measure drop out rate and retention, this phenomenon has only been studied rigorously by Lee and Hoh [35] and Musthag *et al.* [44]. The former was studied in the context of recurrent reverse auctions and the latter in the context of uniform, variable, and hidden micropayments.

D. Working Autonomous, Intelligent Agents

Despite the abundant literature in this area, we did not find any work in which the incentive system is built on a platform of intelligent agents. However, several schemes reviewed may be easily extended to this environment.

E. Economic Models

The review found only two proposals of data markets, the works of Liu *et al.* [36] and Lee and Hoh [35], respectively. The former is based on microeconomics and includes the participation of an auctioneer and n bidders (i.e., users). These data markets include incentive mechanisms, allocation of resources, assignment of rewards, and control of drop out and retention. The latter involves dynamic resource allocation and rewards as well as the use of energy as a mechanism to decrease the users' reservation wage. Furthermore, factors such as QoI satisfaction and network operator profits also play a role in computing user rewards.

F. Incentives With Privacy-Preserving Mechanisms

Privacy-preserving mechanisms aim to guarantee that a user's data cannot be associated with the user's identity [25]. Unfortunately, this aim is in direct conflict with the goal of capturing high-quality data. For example, the location data often captured by CS systems can also reveal identity (e.g., by inadvertently revealing the user's home). Other data attributes could reveal specific groups to which the user belongs, effectively narrowing the set of possible user identities. Thus, privacy mechanisms can offer good privacy protection or good data quality but cannot offer both at the same time. There is a need to balance the quality of data captured against the anonymity of the user. For instance, if privacy-preserving mechanisms modify or mask the user's location, then it is unclear if samples come from the requested location. Further, incentive mechanisms dependent on location are also affected. For example, an incentive mechanism might pay higher incentives for regions with older data. However, due to location masking, users selected from a region may, in fact, be in a different region. The data they report will thus be associated with the wrong location in the database, and the system may overpay or underpay for the data received. Therefore, the challenge is to protect participant privacy while guaranteeing a set level of data quality, especially when used along with an incentive mechanism.

VI. Conclusion

This paper has offered several contributions. First, to the best of our knowledge, this is the only work to date that surveys the state-of-the-art in CS incentive mechanisms. Second, we have proposed a set of design issues which can be used as metrics to evaluate CS incentive mechanisms. Third, we have introduced a tree-level taxonomy of CS incentive mechanisms, primarily defined by the approach used to motivate user participation. Finally, we have proposed a set recommendations and directions for future research. Therefore, this paper serves as an important tool for the design and selection of incentive mechanisms for CS applications.

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