Research Article

Reputation-Based Incentives for Data Dissemination in Mobile Participatory Sensing Networks

Jie Li,[1] Xingwei Wang,[1] Ruiyun Yu,[1] and Rui Liu[2]

[1]*Northeastern University, Shenyang 110819, China*
[2]*Hong Kong Polytechnic University, Kowloon, Hong Kong*

Correspondence should be addressed to Jie Li; lijie@mail.neu.edu.cn

The ever-more-capable smart mobile phone gave birth to a novel sensing paradigm, participatory sensing. In the application environment of mobile participatory sensing networks, mobile equipment is usually weakly connected. Due to uncertainty of connection, mobile nodes sometimes need encounter opportunities to accomplish data communication and transmission. However, the participants' reluctance would diminish their enthusiasm if there is no incentive mechanism. To address this nontrivial issue, we propose reputation-based incentive schemes to motivate participants to disseminate reliable data in participatory sensing system, named RIDD, while minimizing incentive cost for maintaining sufficient number of reliable participants. When an intended receiver receives the data packet from a participant, the receiver authorizes the participant by an acknowledgment message within an encryption code automatically generated by the data packet, which serves as a proof of successful data delivery. RIDD evaluates participants using reputation degree calculated according to the encryption code, encouraging reliable participants to keep being interested in the participatory service with rewards. We conduct simulations in different scenarios. The results show that RIDD remarkably increases the winning probability of participants who disseminate accurate data and reduces the cost for retaining sufficient number of reliable participants.

1. Introduction

Smart phones are penetrating human life and over 1 billion people make use of them globally. With the high processing power, sophisticated embedded sensors, larger storage support, and full networking capability, the mobile phones promise to support services like information sharing, mobile social networking, environmental detection, and traffic monitoring by integrating ubiquitous sensing, large-scale data collection, and cloud computing. These are the advantages that gave birth to a novel and exiting sensing paradigm, participatory sensing [1, 2]. Several universities and institutes have done relevant research in this area and a plethora of exciting participatory sensing applications have emerged in recent years. PEIR [3] is a participatory sensing application which tries to estimate the environment impact to their action based on their location information provided by mobile phone. CarTel [4] is a vehicle participatory sensing system designed to collect, process, deliver, and visualize traffic data

from vehicles. Bubble-Sensing [5] is a new sensor network abstraction that allows mobile phones users to create a binding between tasks (e.g., take a photo or sample audio every hour indefinitely) and the physical world at locations of interest, which remains active for a duration set by the user.

The mobile nodes communicate with each other via cellular base stations in the traditional cell networks. With the increasing demand for faster data connectivity, different wireless technologies have been deployed in the last decade, creating a heterogeneous wireless environment. Such wireless diversity is mainly composed of 2G/3G/4G cellular base stations, IEEE 802.11 hotspots, and Community Networks [6]. Mobile participatory sensing network is often created for a local community in which the participants have frequent interactions. Smart phones can communicate with each other and exchange sensing data via their short range radios (e.g., WiFi, Bluetooth, Zigbee, and WiFi-direct). Such mobile device-to-device data transmission can increase network performance and reduce communication cost for both service

providers and individual users. A crucial issue is how source nodes choose forwarding participants. The goal is to choose a participant which delivers a message to destination with high probability. Except for that goal, reliable data delivery is also very important in the realistic application environment. However, participants will eventually lose enthusiasm to remain active in participatory sensing applications without being fairly rewarded. Namely, participants may drop out unless the reward is greater than their expectation. Furthermore, there are some malicious participants who will disseminate bogus sensing data when the realistic participatory sensing networks are deployed. Malicious participants may supplant normal ones and it may be worse when they collude with each other. In such circumstances, normal participants drop out and malicious ones will control the system without hesitation. To fill this gap, we design an incentive mechanism to motivate participants to disseminate reliable sensory data.

Within the scope of this paper, we propose the reputation-based incentives for data dissemination (RIDD) to categorize and motivate participants, while minimizing incentive cost for maintaining sufficient normal participants which always disseminate reliable sensing data.

RIDD first analyzes the disseminated data to evaluate the trustworthiness of participants using accumulated reputation degree. Then a multidimensional reverse auction will be performed by RIDD and reputable participants who bid lower price will win the reward. Furthermore, RIDD will adjust each participant's bid price and increase winning probability of loser in the next auction round according to their reputation level.

The following is a list of our main contributions.

(i) We establish reputation model to evaluate the trustworthiness of participants by reputation degree. The reputation degree is calculated according to reliability of disseminating data. High reputation degree reflects accumulation of good historical participations and vice versa.

(ii) We design reputation-based incentive scheme (RIS) for data dissemination in mobile participatory sensing networks. RIS can remarkably decrease incentive cost for maintaining sufficient participants through multidimensional reverse auction where bid price and reputation degree are both considered. Virtual coupon is introduced in RIS in order to increase winning probability of the reputable participants in the next auction round.

(iii) We design data dissemination algorithms based on RIS, named RIDD. RIDD is an efficient data dissemination algorithm to encourage mobile nodes to continuously participate in data dissemination activities and provide reliable data messages with low transmission cost and high delivery ratio.

The remainder of this paper is organized as follows. In Section 2, related works about data dissemination algorithm, reputation model, and incentive scheme are illustrated. Section 3 gives details of RIDD. In Section 4, RIDD is evaluated in various simulations. Finally, we conclude this paper in Section 5.

2. Related Work

2.1. Data Dissemination in Mobile Participatory Sensing Networks. Data dissemination in the mobile participatory sensing networks has opportunistic and community characteristics. The mobile nodes transmit data messages by the store-carry-forward way. The mobile node utilizes communication opportunities obtained from node movement to relay packets. Such data dissemination schemes are proposed in social opportunistic networks applications. The data dissemination in PeopleNet [7] is based on epidemic dissemination. A contact aware duplication algorithm [8] is proposed for data sharing in interconnectivity mobile network. In [9], the scheme is proposed for information sharing among people onboard vehicles. However, all of these dissemination schemes assume nodal cooperation in opportunistic networks.

Selfishness of mobile nodes has been investigated in the context of mobile ad hoc networks. Their ultimate goal is to stimulate nodes to help by forwarding packets for others. However, these incentive approaches are not directly applicable in DTNs. In [10–13], these schemes have reputation-based or credit-based incentive schemes. In all of these scenarios, receivers are beneficiary and paid for data delivery services in one way or another. Clearly, they are different from the participatory sensing data dissemination application studied in this work, where individual nodes can be data providers and push data packets to a set of receivers. All these schemes cannot preserve the reliability of the data message and prevent the malicious behaviors of the participants.

In [14], TB-SnW is a data dissemination algorithm designed based on trust management in delay tolerant networks (DTNs) that suffer from black hole attacks, which solves the issue that malicious nodes discard the data packet but not the integrity and security of the transmitted data. RCAR [15] is a reputation-based approach to tolerate misbehaving Carriers in DTNs, and there is no global agreed notion of reputation. In [16], if a relay node fails to show successful relay proofs, it is excluded from future communication. However, the permanent penalty on selfishness leads to the participants reluctant to join the participatory service.

An incentive mechanism based on being self-interest-driven (SID) is presented in [17], where cooperation between selfish nodes for ad dissemination in autonomous mobile social networks is stimulated. It provides virtual checks schemes to reward the mobile nodes in an autonomous mobile social network. We will compare SID with RIDD in Section 4.

2.2. Incentive Scheme. In order to stimulate the mobile nodes to provide reliable data dissemination service, the incentive scheme is designed in our data dissemination algorithm. Generally, incentive schemes can be classified in to two categories: *Extrinsic Incentive* and *Intrinsic Incentive*. Extrinsic Incentive involves financial rewards [18, 19] and reputation

[15]. Reversely, Intrinsic Incentive confines to fun interest [17], self-improvement, self-expression, and charity.

What we consider as the most relevant work is incentive mechanism of financial rewards. In this way, the active and well-behaved nodes can obtain some remuneration for their participation [20]. The mechanism of distinguishing services mainly provides different level services to sensors according to their behavior [21]. The mechanism, by its very nature, offers more resources and services to incentive reputable nodes.

Reverse auction is a special form of offering rewards. In a general auction, buyers become bidders and the seller is an auctioneer. By comparison, in a reverse auction there is a single buyer that becomes an auctioneer while many sellers become bidders. In terms of bidding sides, auctions can also be classified as single or double ones. In a single auction, only one side of participants can bid. On the other hand, in a double auction, both sides of participants can bid.

All abovementioned auction types use bids that comprise only price, so we call it one-dimensional reverse auction. In contrast, a multidimensional reverse auction allows bidders to bid on various attributes beyond the price. Since the auctioneer selects winners based on all bidding attributes, the overall utility of a bid should be computed following various utility functions. General procedures for multidimensional auctions in e-markets have been described in [22].

Recent studies in [19] have proposed a motivation system, named the reverse auction based dynamic price incentive mechanism with virtual participation credit (RADP-VPC).

To the best of our knowledge, few studies address incentive mechanisms with multidimensional reverse auction in participatory sensing system well. RIS is the reputation-based incentive system where a multidimensional reverse auction is introduced with considering participants' reputation.

2.3. Reputation Model. Reputation model is the measure of weight quality of the data services, which have been used in ad hoc wireless networks [23–26]. In [23, 24], reputation model based on game theory attempted to address the selfish routing problem in such networks. In [25, 26], Bayesian analysis is used to formulate a similar problem and the resulting reputation models are shown to counter any misbehaving nodes. Bayesian reputation models are quite flexible and can be adapted with relative ease in different types of applications and environments [27, 28]. The reputation frame work proposed in [29] makes use of Beta reputation [27] for associating a reputation score with each sensor node in a traditional embedded wireless sensor network. However, it takes a less aggressive approach in penalizing participants that contribute corrupted data.

To the best of our knowledge, a few research works are conducted on reputation in mobile participatory sensing networks. Huang et al. in [30] implements a noise monitoring system to identify corrupted noise data. However, the system only focuses on the sensing data provided by participants in current monitoring application without considering accumulated reputation of participants. Haofan et al. proposes using reputation management to classify the gathered data and

provide useful information for campaign organizers and data analysts to facilitate their decisions [18]. However, the author just provides a simple reputation method and cannot adapt to the changeable environment when participatory sensing system deploys in the real world.

All abovementioned reputation models are not used in the data dissemination service in mobile participatory sensing networks and are not combined with the incentive schemes to measure the integrity and security of the delivering data. In our algorithm, reputation model is established to weigh the reliability of participants and provide evidence to the incentive scheme which gives rewards to recruit more reputable participants to finish the data dissemination service.

3. Reputation-Based Incentive Mechanism

In this section, we propose the reputation-based incentives for data dissemination (RIDD) in the context of mobile participatory sensing systems.

3.1. System Overview. A mobile participatory sensing network is a mixture of an opportunistic network and a centralized infrastructure (as shown in Figure 1). The opportunistic network consists of a set of intermittently connected mobile nodes. The data exchanged in this scenario is assumed to be of high magnitude, and data transmission can only occur between mobile nodes by short range communication during the contact opportunity. The centralized infrastructure consists of a number of wireless access points (APs) and a backbone connecting the APs. Mobile nodes (carrying smart devices) can only access the network when they are walking into the transmission range of any AP. The centralized server is merely responsible for executing the reputation-based incentive scheme (RIS), only exchanging control messages with mobile nodes. Each mobile node can act as a sensing data provider, a participant to disseminate the sensing data, or a data receiver. The mobile nodes can play different roles or act those roles simultaneously. A sensing data provider senses the data from his environment according to what the system desires. The participant is the mobile node who applies for participating in the data dissemination service. The participant obtains data from the provider and then transforms the data message to the data receiver or to the next mobile nodes.

The mixture network model enhances traditional opportunistic networks with the centralized infrastructure which takes good advantage of existing AP assets but does not burden current network. The control message is very tiny compared with the data message, so the transmission overhead of the control message can be negligible. The APs are deployed according to the density of the mobile nodes. For example, in the campus scenario, each room in the teaching buildings and library deploys at least an AP router. Therefore, the system model can avoid the hotspot problem.

The RIS server provides the services on reputation calculation and the incentive mechanism execution. The RIS server
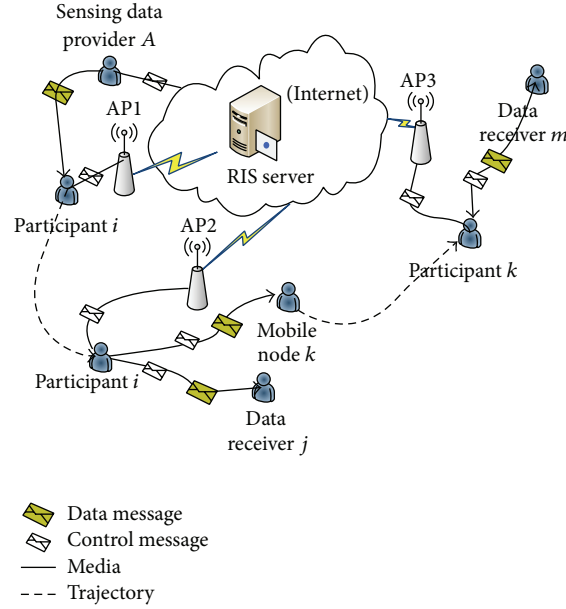
FIGURE 1: Data dissemination model based on RIS.

transmits only control messages but not data messages. The data messages are delivered by the participatory nodes.

3.2. Reputation-Based Incentive Schemes.

In the data dissemination systems, the reliable data dissemination is vital to the quality of service. The schemes should be designed to preserve the integrity and reliability of the data message. In the proposed system, the data message is transferred between the participants and the receivers. If the participant corrupts the data message or discards the data message, only to cheat the system rewards, the RIS server could not detect the malicious behaviors of the participants.

3.2.1. The Framework of RIS.

In order to tackle issue of malicious behaviors of participants, the encryption code generation scheme is proposed. When the participant transmits the data message to the receiver node, the receiver node will give feedback by an ack message to the participants.

The format of the ack message is ack<*copy id, data id, digital signature, encryption code*>. *Digital signature* is generated by the receiver node, which is the identification of the mobile node. This metric is used to estimate the data discarding behavior of the participant. If the participant really finished a data transmission, it can get the digital signature of the receiver. *Encryption code* is generated by the data provider. The encryption code can be a hash code of the data, which is uniquely represented by the original data. If the data have been distorted or corrupted, the encryption code will change. In the proposed system, the RIS server is authorized to be creditable. Finally, the participant accomplishes the task and submits all the feedback messages to the RIS server. The RIS server will calculate the encryption code set categorized by the data id to give out the reputation of the participant.

Figure 2 depicts the framework of RIS. Generally, data dissemination request is sent (e.g., by smart phone or PDA) to the participants through RIS server in mobile participatory sensing networks. After data dissemination, each participant submits the feedback messages to the server and RIS residing in the server processes all data obtained from participants.

Firstly, encryption code will be uploaded to the Reputation Module where the reputation score of the participant is produced, respectively. After that, the reputation degree can be successfully derived based on game theory.

Then, a multidimensional reverse auction in the Incentive Module selects winners in terms of Rank Prices which are calculated based on participants' bid prices and the virtual coupon they possess.

Finally, the participants with lower Rank Prices win out, get reward, and reset their virtual coupon to zero. Nevertheless losers will obtain virtual coupon to raise their winning probability.

3.2.2. Reputation Model.

In general, the number of normal participants is usually larger than that of malicious participants in a target field, so we choose the density-based outlier detection algorithm proposed in [31] to preprocess the encryption code set of disseminating data $S = \{s_1, s_2, \ldots, s_n\}$ received from n participants delivering the same data message. The details are illustrated in

$$A = \sum_{i=1}^{n} M_i s_i,$$

$$M_i = \frac{1/\left(\left(s_i - A\right)^2 / \sum_{i=1}^{n} \left(s_i - A\right)^2 + \varepsilon\right)}{\sum_{j=1}^{n} \left(1/\left(\left(s_i - A\right)^2 / \sum_{i=1}^{n} \left(s_i - A\right)^2 + \varepsilon\right)\right)}. \tag{1}$$

As shown in **Figure 2**, the algorithm is iterative in nature. At first, it defines and initializes $M_i = 1/n$. A and M_i
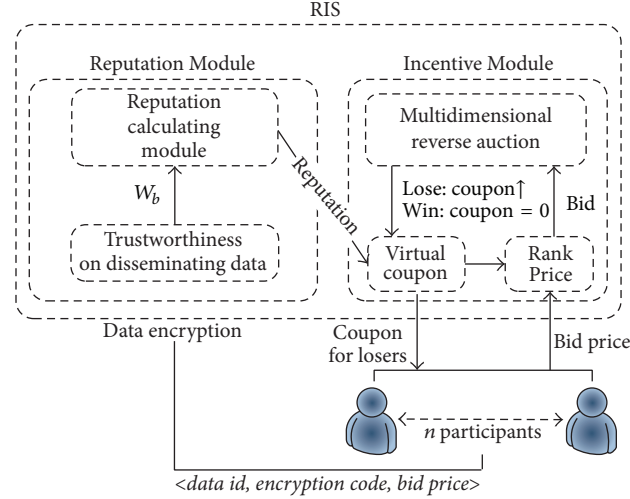
FIGURE 2: Framework of RIS.

are computed in each iteration. M_i^f equals M_i^{l+1} when the convergence $|M_i^{l+1} - M_i^l| < \eta$ is observed in the $(l + 1)$th iteration.

It is obvious that tighter convergences could be chosen to produce more accurate result according to specific scenarios. ε is a small positive constant for adjustment and more discussion can be found in [31].

As mentioned in Algorithm 1, normal participants are usually more than malicious ones in mobile participatory sensing networks. Consequently, the majority of participants who provide similar sensing data will have higher M_i^f. This takes the fact that most participants generate relatively accurate sensing data.

However, in particular circumstances, the number of malicious participants would be larger than that of normal ones in sensing field which will affect overall data accuracy. It may lead to fatal error when making decisions based on such corrupted data provided by malicious ones in the networks. To tackle this issue, the source data node can generate the encryption code to the RIS server.

After several rounds, a participant will present its trustworthiness through its historical behaviors. The trimmed-mean method [32] is introduced to reflect the long-term trends accordingly. The method is a statistical measure of central tendency and involves the calculation of mean value after discarding given parts of a probability distribution or sample at the high and low ends and typically discarding an equal amount of both.

The reputation score $R = \{r_1, r_2, \ldots, r_n\}$ is computed based on historical M_i^f using the trimmed-mean method and is depicted in

$$r_i = \frac{M_{i,([m\sigma]+1)}^f + M_{i,([m\sigma]+2)}^f + \cdots + M_{i,(m-[m\sigma])}^f}{m - 2 \cdot [m\sigma]}, \quad (2)$$

where m represents the number of observations and $\sigma \in [0, 1/2)$.

3.2.3. Incentive Module.
To motivate participants, a multidimensional reverse auction is introduced in the Incentive Module. The objective of RBPIA is to maintain adequate number of participants for desired service quality while minimizing incentive cost by preventing cost explosion during the multidimensional reverse auction.

Intuitively, participants who bid lower price are more likely to become winners in one-dimensional reverse auction, as shown in Figure 3. However, the participants who always lose in auction may drop out. As a result, the winners can manipulate subsequent auctions and increase bid price to maximize their profits.

To maintain fair competition and prevent incentive cost explosion, enough participants should participate continuously in reverse auctions of RIS. For this goal, the proposed Incentive Module provides a novel winner selection strategy using virtual coupon and reputation degree.

Participant (i.e., bidder) i will receive virtual coupon as a reward when they lost in the previous auction round to increase winning probability in the next round. The virtual coupon $D = \{d_1, d_2, \ldots, d_n\}$ can be defined as

$$d_i = \begin{cases} \gamma \cdot r_i & \text{if participant } i \text{ lost in the previous round} \\ 0 & \text{otherwise,} \end{cases} \quad (3)$$

where γ denotes the amount of virtual coupon and r_i is a weight created by the Reputation Module. Hence, whenever participant i loses in an auction round, an amount of coupon γ weighted by reputation degree r_i equals virtual coupon d_i. Reputable participants can obtain more virtual coupon.

The virtual coupon d_i is set to zero whenever participant i won or dropped out in the previous auction round. The virtual coupon can only be used for decreasing bid price, thus increasing winning probability of participant for current auction round.

```
Input: Number of participant N = {1, 2, . . . , n}, encryption code set S = {s₁, s₂, . . . , sₙ} of n participants
Output: M = {m₁ᶠ, m₂ᶠ, . . . , mₙᶠ}
(1)  for i = 1 to n do
(2)     mᵢ ← initial_value;
(3)     while convergence do
(4)        Compute A using (1);
(5)        for t = 1 to l do
(6)           Compute mᵢᵗ using (2);
(7)        end
(8)        convergence ← mᵢᵗ − mᵢᵗ⁻¹ (mᵢ⁰ = mᵢ)
(9)     end
(10)    mᵢᶠ ← mᵢᵗ
(11) end
```

ALGORITHM 1
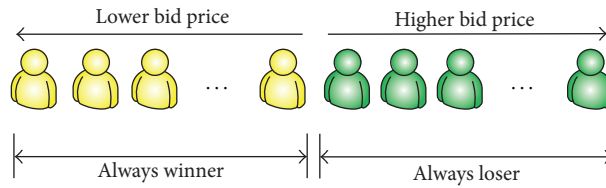
FIGURE 3: Winners and losers in one-dimensional reverse auction.

Two types of bid prices are defined. One is actual bid price and the other is Rank Price. The actual bid price b_i is claimed by participant i and the Rank Price p_i can be defined as

$$p_i = b_i − d_i. \tag{4}$$

In the proposed Incentive Module, the Rank Price p_i is used for selecting winners in each auction round and RIM increases the winning probability of the bidder by decreasing Rank Price using virtual coupon.

Even participants who bid higher price can be winners by participating continuously (as shown in **Figure 4**). Therefore, RIS encourages continuous participation of participants in the system.

3.3. The Process of RIDD. The reputation degree is calculated by the RIS server; it will not influence the data transmission event. In order to increase the opportunity to transmit the data, each participant can obtain the data messages. The RIS server will estimate the reputation of every participant. If the participant misbehaved, it will be punished with no rewards. Otherwise, the participant with high reputation will gain rewards and also obtain the virtual coupon. Therefore, the high reputation the participant has, the more rewards the participant gains.

The data dissemination algorithm adopted the LOPSI [33]. It is deployed in the same scenario; it has a location prediction server, which can integrate with the RIS server; each node will choose a node with the max transmission probability to transform the data.

The LOPSI algorithm is a probabilistic routing protocol combining location prediction and the ant colony optimization. It firstly predicts possible locations of relay nodes and

destinations in successive time series. The mobile nodes calculate intimacy (contact frequency) with potential relay nodes using ACO and then make a forwarding decision based on node intimacy and probabilities of node mobility. The transmission probability is calculated by

$$p_{sf}^d = \gamma * p_{R_{sf}}^d + \delta * p_{L_{sf}}^d, \quad \gamma + \delta = 1, \tag{5}$$

where $p_{R_{sf}}^d$ is the forwarding probability obtained from the intimacy calculation of mobile nodes and $p_{L_{sf}}^d$ is the forwarding probability obtained from location prediction schemes.

The control messages used in the system are defined as follows.

Definition 1. SREQ is the service request message in which the data source node is sent to the RIS server. The format of SREQ is SREQ<*data id, category id, source address, destination list*>.

The data id uniquely represents the data message. The category id is the description of the content of the data message. Source address is the location information of the data source node. In the specific application environment, it can be AP address. The source address is used as a broadcast scope by the RBPIA server that broadcasts service recruiting messages. The destination list involves the destination node addresses where the data message will be sent. The destination node is usually the data aggregation server or the node who desires the data message.
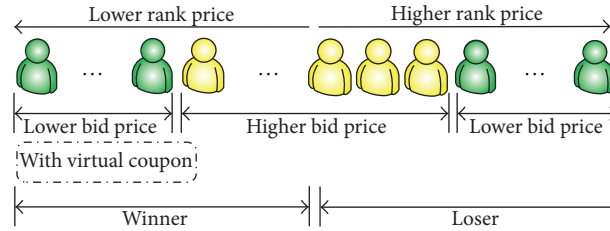
FIGURE 4: Winners and losers in multidimensional reverse auction with virtual coupon.

Definition 2. PAT is the participatory message that the mobile node sends to the RIS server. The format of PAT is PAT<*participatory id, bid price, copy number, additional data*>.

Additional data can be the transmission probability of the node to the source node. The bid price equals the consumption that the participant transmits one data copy. The system will pay more than the participant consumes, so the mobile nodes are willing to participate in the service. The maximum number of data copies one participant can disseminate equals copy number.

The data dissemination process is as follows.

Step 1. The data source node sends a SREQ message to the RBPIA server. When the data sensing node finishes the data dissemination service, it will send the encryption code of the data message to the RBPIA. The encryption code may be the hash code generated by the data message. It is used to calculate the trustworthiness on disseminating data.

Step 2. The RBPIA server broadcasts the SREQ messages to the mobile nodes nearby the source address. The broadcast domains in the campus scenario are coverage areas of the communication radius of the APs to which the data source node connects.

Step 3. When the mobile node N_i receives the SREQ message from the RBPIA server and would like to participate in the data dissemination service, N_i will send the control message PAT to the RIS.

Step 4. If mobile node N_i wins the bid round, it becomes the participants.

Step 5. When participant i encounters a mobile node, the former firstly transmits the destination address to the latter. If it is the receiver, the data message will be directly delivered. And the participant will get an ack message from the receiver. Otherwise, if the node meets a mobile node who has a higher transmission probability than the participants, the former will transform the data message to the latter. And the latter node returns an ack message to the participant who would like to forward the data message.

Step 6. The participant I transmits a data message to the data receiver, it will get an ack message. The accumulated ack messages will totally send to the RIS server and get back the rewards.

Step 7. If the mobile node wants to be the participant, it directly sends PAT message to the RIS server; the communication cost of send a PAT message is negligible. If the mobile node agrees with the bid price that the former participant gains, it receives the data message and gets several data copies from the former nodes and becomes a participant.

Step 8. When participant i disseminates all the data copies, it will send the total ack messages to the RIS, and the RIS pays for the participant according to the results of reputation calculation.

4. Performance Evaluation

The purpose of the experimental section is to evaluate RIDD in two scenarios and illustrate its properties.

4.1. Performance Comparison Algorithms. Spray and Wait [34] is chosen as the baseline for comparison. It is a leading opportunistic routing algorithm, without consideration of selfishness. Under Spray and Wait, a number of copies are sprayed into the network and then the network "waits" till one of these nodes meets the destination. Since Spray and Wait does not consider selfishness of mobile nodes, we implement its two variants. The first which is denoted by "SaWselfish" is under the assumption that all nodes are selfish. Thus, a node only receives its desired data message directly from the source data node. In the other variant named "SaWcooperative," we assume that nodes are cooperative and altruistic. A node always chooses the most valuable data messages to carry for others after satisfying its own convenience, considering its resources and routing.

SID is a self-interest-driven incentive scheme to stimulate cooperation among selfish nodes for ad dissemination in autonomous mobile social networks. A virtual check is included in each ad packet. When an intended receiver receives the packet for the first time from an intermediate node, the former authorizes the latter a digitally signed check, which serves as a proof of successful ad delivery. Multiple copies of a virtual check can be created and signed by different receivers. When a node that owns a signed check meets the ad provider, it requests the provider to cash the check. Both

Table 1: Simulation parameters.

Parameter	Value
Simulation time	12 h
Field area	4500 m ∗ 3400 m
Scene	NEU campus
APs	50
Movement speed for cars	2.7–13.9 m/s
Number of cars	40
Movement speed for pedestrians	0.5–1.5 m/s
Number of pedestrians	160
Maximum transmission range	100 m
Maximum queue size	200 data packet
Packet size	500 KB–1 MB at random
Frequency of creating packets	From 25 s to 35 s at random
Maximum number of copies	8

ad packets and signed checks can be traded among mobile nodes.

4.2. Simulation Setup. The representative participatory sensing data set is UCSD WTD data set [35], which is employed in our simulation scenarios. Note that the recent work studying the nature of human mobility has proved that suitable movement models can sufficiently present the behavior of human mobility [36]. The model of mobility pattern deployed in our platform is SPMBM model [37], which is a mobility model that integrates temporal and spatial relationships and selects the shortest path for the node randomly walking in the map area.

In our simulation, the simulation parameters are shown in Table 1. There are totally 200 mobile nodes that involve 160 pedestrians and 40 cars. The number of sensing data categories is forty. Each node has a default queue size of 200 packets. When a node acts as a data provider, it generates one data message every 10 minutes in a random data category. At the same time, a node is also interested in receiving data in 5 randomly chosen data categories. If the communication range increases and becomes out of the range of APs, the mobile devices can exchange data by the distributed part of LOPSI without using location prediction scheme by different wireless communication techniques including Wi-Fi direct, BlueTooth, and ZigBee. In order to evaluate the performance of the proposed data dissemination algorithms, we conduct a series of experiments under the parameters in Table 1. The First-In, First-Out method is applied on buffer management. The TTL of a packet is set to the expiration time of the data service. It is initially set in the control packet. In the simulation, the TTL is set at variable values in order to compare the performance of the incentive mechanism. The TTL of a packet indicates how long the packet can live in the network.

4.3. Evaluation Metrics. In order to compare the incentive schemes, the proposed mechanism in [19] is deployed in the simulation. Specifically, as shown in (6) and (7), participants

drop out or rejoin in auctions based on return on investment (ROI) and expected return on investment (EROI), respectively.

4.3.1. Return on Investment. The value of ROI is derived as follows:

$$\text{ROI}_i^r = \frac{e_i^r + \beta_i}{\rho_i^r \cdot t_i + \beta_i}, \qquad (6)$$

where ρ_i^r denotes the number of participation of participant i until current participation round r. Hence, $\rho_i^r \cdot t_i$ and e_i^r denote the expected minimum reward and the actual earned reward of participant i, respectively. The β_i denotes participant's tolerance period. A larger β_i makes the ROI value decrease slowly. Therefore, the ROI value is the ratio of the earned reward (i.e., participant's return) to expected minimum reward. We use each participant's ROI value to decide whether he/she drops out of the reverse auction for participatory sensing system. Each participant drops out when the ROI value goes below 0.5, which we set to a satisfaction threshold. In the simulation we assign different tolerance period β_i so that each user has different minimum ROI threshold for dropping out of the reverse auction. Consider the following:

$$\text{EROI}_i^{r+1} = \frac{e_i^r + \varphi_r + \beta_i}{(\rho_i^r + 1) \cdot t_i + \beta_i}. \qquad (7)$$

Moreover, (7) is used for describing rejoining behavior of the dropped out participant. The recruitment mechanism broadcasts the maximum bid value of winners only to the dropped out participants. Hence, the dropped out participants k can calculate the expected ROI value EROI_i^{r+1} for the next participation round $r + 1$ with the revealed maximum bid price of winners in the previous auction of participation. More specifically, φ_r denotes the revealed maximum winning bid price at the previous reverse auction of participatory round r. If the computed expected ROI value of the participants becomes larger than their minimum ROI threshold, the participants rejoin the participatory sensing in order to sell their sensing data. Note that the maximum winning bid price φ_r is only visible to dropped out participants so that we prohibit winners from increasing their bids close to the maximum bid. In the participant behavior model, we assign to participants a set of different tolerance periods β_i of (6) and (7) that is uniformly distributed in the range from 3 to 7. Hence each participant has different minimum threshold for ROI value for dropping out of the multidimensional reverse auction in participatory sensing system.

4.3.2. Utility Function. According to the utility function in [38], the adaptive bidding behavior of auction in simulation is represented as follows. If a participant loses in the previous auction round, the bid price will be decreased by 20% of current bid price for a next participation round. Conversely, if a participant wins in the last auction round, the bid price will arise by 10% of the current bid price or stay at the current bid price with equal probability for next round. For

TABLE 2: Disseminating data provided by participants.

Participant	Disseminating accurate data
Normal	90–100%
Malicious	10–20%

TABLE 3: Participant composition in two scenarios.

Scenarios	Normal	Malicious
A	90%	10%
B	50%	50%

initial bids of participants, we randomly generate the first bid of each participant uniformly distributed between true valuation and its 150%. To observe the effect of participant recruiting mechanism, when the dropped out participant tries to rejoin based on expected ROI value $EROI_i^{r+1}$ for the next auction round $r + 1$, a dropped out participant k tosses the coin and randomly decides to join or not if the expected satisfaction value of next reverse auction round is larger than the participant's ROI threshold.

4.3.3. Malicious Behavior.

We classify the participants into two categories: normal participant and malicious participant.

As shown in Table 2, normal participants upload accurate data in 90–100% of participations and bid according to their true valuation (i.e., the consumption for disseminating the sensing data).

Malicious participants are supposed to intentionally provide corrupted sensing data (only provide accurate data in 10–20% of participations) and bid normal prices. The bidding behaviors of malicious participants do not follow utility function.

We run simulations in two scenarios (marked as scenario A and scenario B), and 200 participants are involved in the simulations (see Table 3).

4.3.4. Performance Metrics of Data Dissemination Algorithms.

The delivery ratio is defined as the ratio of the total number of accurate delivered data messages (the corrupted data messages and the discarded ones are excluded) to the total number of data messages that should be disseminated to the corresponding receivers.

The average latency measures how long a receiver node waits to get the data message packet.

The transmission cost is defined as the ratio of the total number of transmissions to the total number of delivered messages. Lower overhead means less traffic in the network and lower resource consumption. In the proposed system, the control message is much smaller than the data message and, therefore, its transmission cost is negligible.

The incentive cost of the system, noted as C, measures the rewards paid to the participants. It is defined in

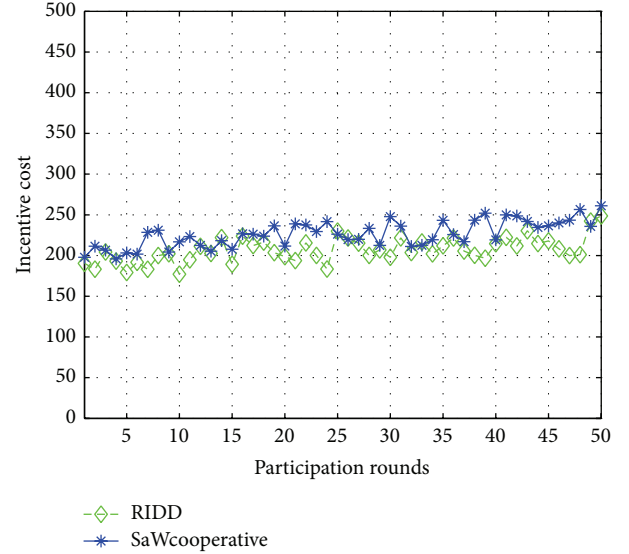$$C = \sum_{i=0}^{n} \frac{Q_i \times B_i}{S_i}, \qquad (8)$$

FIGURE 5: Incentive cost of RIDD and SaWcooperative in scenario A.

where n is the number of the total participants in the system, Q_i is the total number of data messages that participant i sends, S_i is the total number of accurate delivered data messages that participant i sends, and B_i is the rewards the system pays to the participant i. Therefore, the more accurate delivered data messages and the lower rewards contribute to less incentive cost of the system.

4.4. Simulation Results

4.4.1. Incentive Cost.

We run simulations for 50 rounds in scenario A and scenario B (as shown in Table 3). We compare the RIDD and SaWcooperative under the same reward values. Figures 5 and 6 depict the tendency of incentive cost in 50 participation rounds.

In scenario A, both RIDD and SaWcooperative mostly select normal participants, and there are no malicious participants in this scenario, so the two schemes both keep low incentive cost. In contrast, as we can see from Figure 6, incentive cost of SaWcooperative increases dramatically from about round 20 in scenario B due to existence of malicious participants. Such phenomenon means that SaWcooperative cannot cope with malicious participants. The malicious participants disseminate the corrupted data. The system cannot distinguish the accurate data messages and the corrupted ones. Therefore, the system pays for all the delivered data messages, which results in high incentive cost.

4.4.2. Recruiting Reputable Participants.

The recruiting mechanism is introduced into both RIS and RADP-VPC. We simulate rejoining behaviors of dropped out participants in two scenarios. The recruiting mechanism helps to increase the number of active participants and reduce incentive cost. Specifically, more reputable participants rejoin a
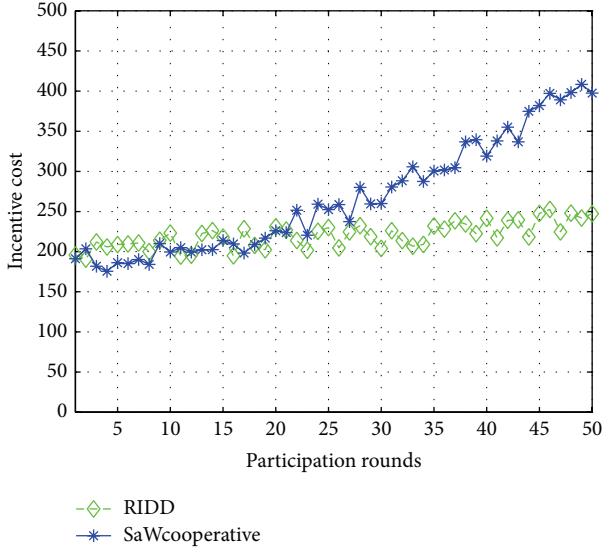
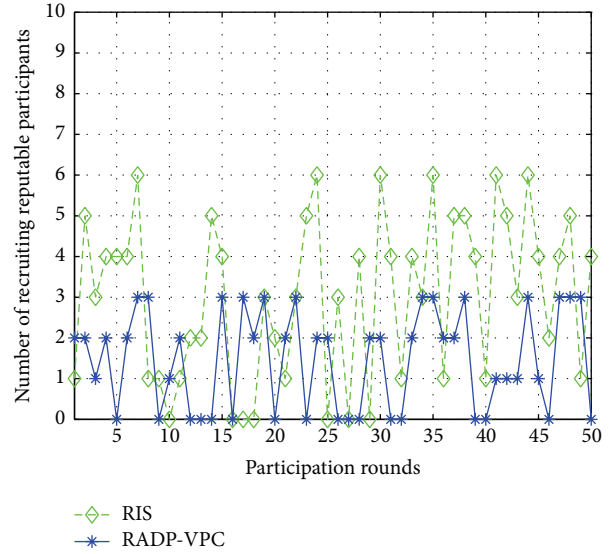FIGURE 6: Incentive cost of RIM and RADP-VPC in scenario B.

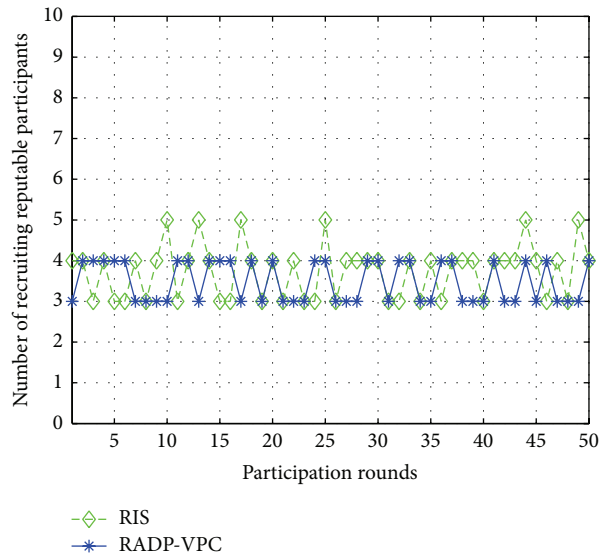FIGURE 8: Number of recruited reputable participants in scenario B.

4.4.3. Evaluation of Delivery Ratio. With the increasing ratio of malicious participants, RIDD performs well until the ratio reaches near 90%. RIDD prevents malicious participants from delivery corrupted data messages. SID has incentive mechanisms to stimulate mobile nodes to participate in the system service, yet without schemes to protect the reliability of the data messages, so the delivery ration decreases sharply. Also SaWcooperative cannot deal with the malicious behavior, so the delivery ratio decreases. Yet the collaboration of the mobile nodes is better than SID, so the decrease ratio is lower than SID. The initial delivery ratio of SaWdelfish is lower than the other schemes as the mobile node rejects to transmit the data message that does not satisfy its convenience and also have a decrease in delivery ratio with the increase of malicious participants (Figure 9).

The data dissemination scheme of SID is like the schemes of PROPHET [37], while RIDD is adopt the LOPSI schemes. In the proposed system, LOPSI and Spray and Wait outperform the PROPHET on delivery ratio, which have been evaluated in [33]. Therefore, the average delivery of RIDD and SaWcooperative is higher than SID.

FIGURE 7: Number of recruited reputable participants in scenario A.

4.4.4. Evaluation of Average Lantency. Figures 10 and 11 illustrate the average latency trend by varying such network parameters as queue size and TTL.

With the increase of the queue size, the average latency also increases. At the initial stage a larger queue decreases the delay in SaWCooperative since it can carry more data messages. However, it simultaneously increases the chance for the data to meet their receivers. A larger queue also means data messages even with a low delivery probability. As for SaWselfish, it decreases the average latency as a large queue size increases its own resources. However, when such packets get delivered, they have already experienced long delay, thus increasing the average network delay. Therefore, the average latency increases. On the other hand, the increase of the
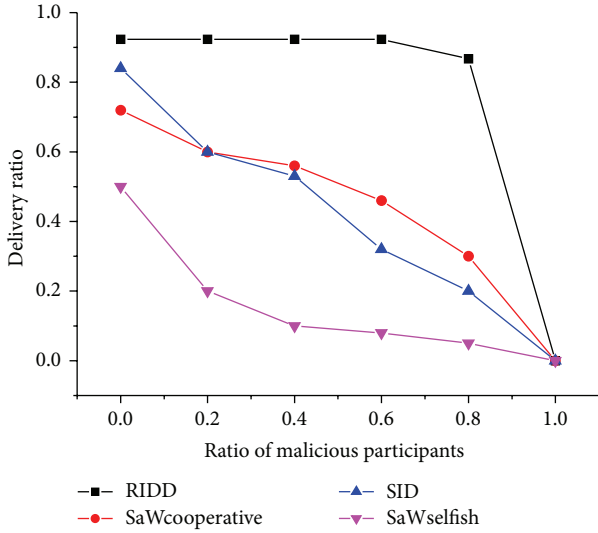
participatory sensing system to prevent the system from being controlled by malicious participants.

Without malicious participants, recruitment of RIS and RADP-VPC can remedy the loss of active participants. As depicted in Figure 7 (scenario A), the number of recruited reputable participants in two schemes is about the same.

RADP-VPC selects winners only based on bid prices and cannot adapt to circumstances with malicious behavior. More specifically, malicious participants will bid lower prices to keep winning and kick normal ones out. RIS selects participants based on the reputation degree and the bid price. In Figure 8 (scenario B) RIS recruits more dropped out reputable participants than RADP-VPC.

FIGURE 9: Delivery ratio varies with the ratio of malicious participants.

FIGURE 10: Average latency trend with increasing queue size.

queue size affects the performance of RIDD and SID only marginally, since RIDD is incentive to forward data for others by the system rewards and SID exchanges the packets based on its self-interest and aims to maximize its rewards. They do not aggressively utilize the increased queue size.

With a longer TTL, all schemes can deliver more packets to the destinations, until the communication capacity of the network becomes the bottleneck and dominates the network performance. As shown in Figure 11, we notice that the average delay of RIDD, SaWCooperative, and SID tends to become stable after TTL increases to 4 hours, while the delay of SaWselfish continues to increase with longer TTL. It means that in RIDD, SaWcooperative, and SID schemes most packets can be delivered within 4 hours, while SaWSelfish needs to keep data messages staying longer in the nodal buffer.

4.4.5. Evaluation of Transmission Cost. Figures 12 and 13 illustrate the transmission cost trend by varying such network parameters as queue size and TTL.

As shown in Figure 12, SaWcooperative gains significantly, because a longer queue allows a node to hold more data packets for a longer time. However, a longer queue results in a surge of transmission cost, because more duplication can be held and transmitted by the mobile nodes. The increase of the queue size affects the performance of RIDD and SID only marginally, since RIDD and SID exchange the messages based on the incentives schemes provided by the system.

As Figure 13 shows, the transmission cost increases with the increase of TTL. This is because extending TTL allows packets to stay longer in the network, which thus has a better chance to be exchanged and duplicated, yielding more overhead. While the transmission cost trend of RIDD stabilizes from 1 hour, since the data message can be delivered
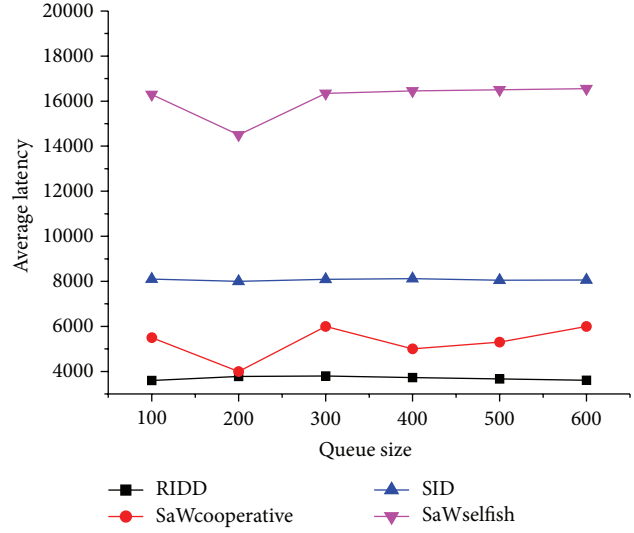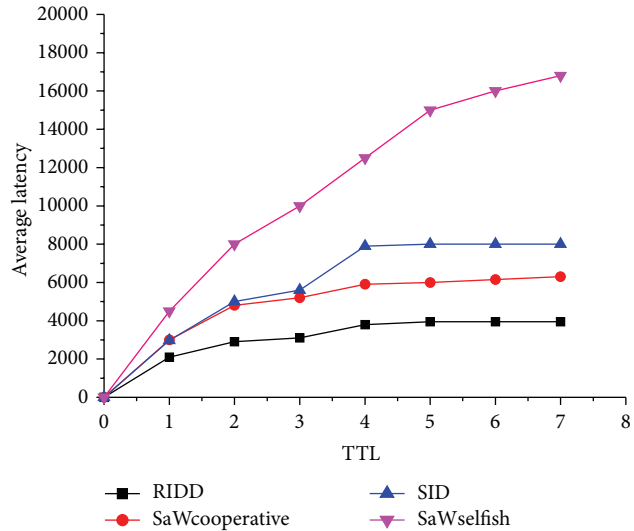
FIGURE 11: Average latency trend with increasing TTL.

to the receiver with a relative high efficiency. The long TTL affects marginally the performance of RIDD.

5. Conclusion and Future Work

In this paper, we designed reputation-based incentives for data dissemination which can be used for motivating participants to deliver reliable data messages in mobile participatory sensing networks. We also address the problem of retaining a desired number of active reputable participants to provide adequate level of service quality with low incentive cost. We presented a set of simulations and highlight the properties of RIDD. The results show that RIDD remarkably increases the winning probability of participants who provide accurate data, preserves the data security in the dissemination process, and performs well in evaluation of the transmission metrics.
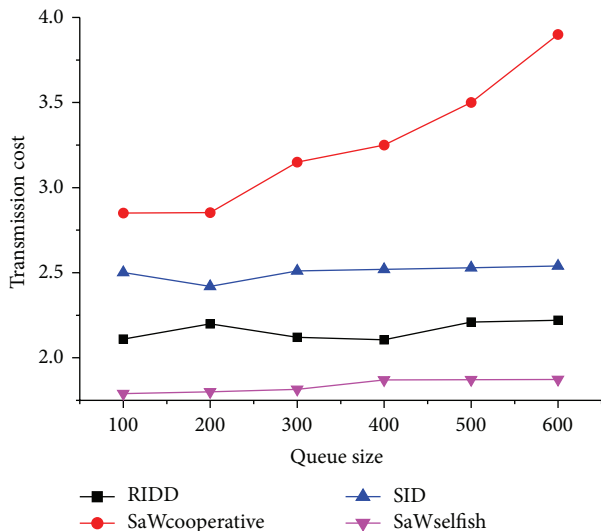
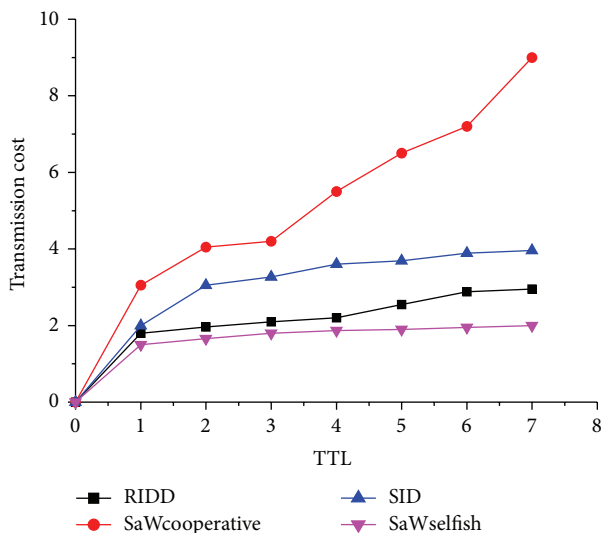FIGURE 12: Transmission cost varying under increasing queue size.

FIGURE 13: Transmission cost under the varying TTL.

In future work, we plan to design an adaptive technique for finding optimal schemes to keep the balance of the participant rewards and the incentive cost.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

Acknowledgments

References

[1] J. Burke, D. Estrin, M. Hansen et al., "Participatory sensing," in *Proceedings of the World Sensor Web Workshop, in conjunction with ACM (SenSys'06)*, Boulder, Colo, USA, November 2006.

[2] G. Han, H. Guo, C. Zhang, and L. Shu, "Parameter optimisation in duty-cycled wireless sensor networks under expected network lifetime," *International Journal of Ad Hoc and Ubiquitous Computing*, vol. 15, no. 1–3, pp. 57–67, 2014.

[3] M. Mun, S. Reddy, K. Shilton et al., "PEIR, the personal environmental impact report, as a platform for participatory sensing systems research," in *Proceedings of the 7th ACM International Conference on Mobile Systems, Applications, and Services (MobiSys '09)*, pp. 55–68, June 2009.

[4] B. Hull, V. Bychkovsky, and K. Chen, "CarTel: a distributed mobile sensor computing system," in *Proceedings of the 4th International Conference on Embedded Networked Sensor Systems (SenSys '06)*, pp. 125–138, November 2006.

[5] H. Lu, N. D. Lane, S. B. Eisenman, and A. T. Campbell, "Bubble-sensing: binding sensing tasks to the physical world," *Pervasive and Mobile Computing*, vol. 6, no. 1, pp. 58–71, 2010.

[6] G. Castignani, J. Monetti, N. Montavont, A. Arcia-Moret, R. Frank, and T. Engel, "A study of urban IEEE 802.11 hotspot networks: towards a community access network," in *Proceedings of the 6th IFIP/IEEE Wireless Days Conference (WD '13)*, pp. 1–8, November 2013.

[7] M. Motani, V. Srinivasan, and P. S. Nuggehalli, "PeopleNet: engineering a wireless virtual social network," in *Proceedings of the 11th Annual International Conference on Mobile Computing and Networking (MobiCom '05)*, pp. 243–257, September 2005.

[8] X. Zhuo, Q. Li, W. Gao, G. Cao, and Y. Dai, "Contact duration aware data replication in delay tolerant networks," in *Proceedings of the 19th IEEE International Conference on Network Protocols (ICNP '11)*, pp. 236–245, IEEE, Vancouver, Canada, October 2011.

[9] U. Lee, J. Lee, J.-S. Park, and M. Gerla, "FleaNet: a virtual market place on vehicular networks," *IEEE Transactions on Vehicular Technology*, vol. 59, no. 1, pp. 344–355, 2010.

[10] L. Buttyan, L. Dora, M. Felegyhazi, and I. Vajda, "Barterbased cooperation in delay-tolerant personal wireless networks," in *Proceedings of the IEEE International Symposium on a World of Wireless, Mobile and Multimedia Networks (WoWMoM '07)*, pp. 1–6, Espoo, Finland, June 2007.

[11] T. Ning, Z. Yang, X. Xie, and H. Wu, "Incentive-aware data dissemination in delay-tolerant mobile networks," in *Proceedings of the 8th Annual IEEE Communications Society Conference on Sensor, Mesh and Ad Hoc Communications and Networks (SECON '11)*, pp. 539–547, June 2011.

[12] X. Xie, H. Chen, and H. Wu, "Bargain-based Stimulation mechanism for selfish mobile nodes in participatory sensing network," in *Proceedings of the 6th Annual IEEE Communications Society Conference on Sensor, Mesh and Ad Hoc Communications and Networks (SECON '09)*, pp. 72–80, Rome, Italy, June 2009.

[13] G. Han, J. Jiang, L. Shu, M. Guizani, and S. Nishio, "A two-step secure localization for wireless sensor networks," *Computer Journal*, vol. 56, no. 10, pp. 1151–1153, 2013.

[14] A. Al-Hinai, H. Zhang, Y. Chen, and Y. Li, "TB-SnW: trust-based Spray-and-Wait routing for delay-tolerant networks," *The Journal of Supercomputing*, vol. 69, no. 2, pp. 593–609, 2014.

[15] G. Dini and A. L. Duca, "A reputation-based approach to tolerate misbehaving carriers in Delay Tolerant Networks," in *Proceedings of the 15th IEEE Symposium on Computers and Communications (ISCC '10)*, pp. 772–777, June 2010.

[16] A. Mei and J. Stefa, "Give2Get: forwarding in social mobile wireless networks of selfish individuals," in *Proceedings of the 30th IEEE International Conference on Distributed Computing Systems (ICDCS '10)*, pp. 488–497, Genoa, Italy, June 2010.

[17] T. Ning, Z. Yang, H. Wu, and Z. Han, "Self-interest-driven incentives for ad dissemination in autonomous mobile social networks," in *Proceedings of the 32nd IEEE Conference on Computer Communications, (INFOCOM '13)*, pp. 2358–2366, April 2013.

[18] Y. Haofan, Z. Jinglan, and R. Paul, "Using reputation management in participatory sensing for data classification," in *Proceedings of the 2nd International Conference on Ambient Systems, Networks and Technologies, (ANT '11)/8th International Conference on Mobile Web Information Systems (MobiWIS '11)*, Ontario, Canada, September 2011.

[19] J.-S. lee and H. Baik, "Dynamic pricing incentive for participatory sensing," *Pervasive and Mobile Computing*, vol. 6, no. 6, pp. 693–708, 2010.

[20] B. Yang and H. Garcia-Molina, "PPay: micropayments for peer-to-peer systems," in *Proceedings of the 10th ACM Conference on Computer and Communications Security (CCS '03)*, pp. 300–310, Washington, DC, USA, October 2003.

[21] A. Habib and J. Chuang, "Service differentiated peer selection: an incentive mechanism for peer-to-peer media streaming," *IEEE Transactions on Multimedia*, vol. 8, no. 3, pp. 610–621, 2006.

[22] M. Bichler, *The Future of e-Markets: Multidimensional Market Mechanism*, Cambridge University Press, 2001.

[23] S. Buchegger and J.-Y. Le Boudec, "Performance analysis of the CONFIDANT protocol (Cooperation of nodes: fairness in dynamic ad-hoc networks)," in *Proceedings of the 3rd ACM International Symposium on Mobile Ad Hoc Networking and Computing (MOBIHOC '02)*, pp. 226–236, June 2002.

[24] P. Michiardi and R. Molva, "Core: a collaborative reputation mechanism to enforce node cooperation in mobile ad hoc networks," in *Proceedings of the IFIP TC6/TCI1 6th Joint Working Conference on Communications and Multimedia Security*, pp. 107–121, 2002.

[25] S. Buchegger and J. Y. Le Boudec, "Coping with false accusations in misbehavior reputation system for mobile ad-hoc networks," EPEL Technical Report NumberIC/2003/31, 2003.

[26] S. Buchegger and J. Y. Le Boudec, "The effect of rumorspreading in reputation systems for mobile ad-hoc networks," in *Proceedings of the Modeling and Optimization in Mobile, Ad Hoc and Wireless Networks (WiOpt '03)*, March 2003.

[27] A. Josang and R. Ismail, "The beta reputation system," in *Proceedings of the 15th Bled Electronic Commerce Conference*, June 2002.

[28] A. Gelman, J. B. Carlin, H. S. Stern, and D. B. Rubin, *Bayesian Data Analysis*, Chapman & Hall, Boca Raton, Fla, USA, 2003.

[29] S. Ganeriwal and M. Srivastava, "Reputation-based framework for high integrity sensor networks," *ACM Transactions on Sensor Networks*, vol. 4, no. 3, article 15, 2008.

[30] K. L. Huang, S. S. Kanhere, and W. Hu, "On the need for a reputation system in mobile phone based sensing," *Ad Hoc Networks*, vol. 12, no. 1, pp. 130–149, 2014.

[31] C. T. Chou, A. Ignjatovic, and W. Hu, "Efficient computation of robust average in wireless sensor networks using compressive sensing," Tech. Rep. UNSW-CSE-TR-0915, 2009.

[32] D. C. Hoaglin, F. Mosteller, and J. W. Tukey, *Understanding Robust and Exploratory Data Analysis*, Wiley-Interscience, 2000.

[33] J. Li, X. Wang, J. Jia, P. Wang, Y. Zhou, and Z. Zhao, "Location prediction-based data dissemination using swarm intelligence in opportunistic cognitive networks," *Mathematical Problems in Engineering*, vol. 2014, Article ID 453564, 15 pages, 2014.

[34] T. Spyropoulos, K. Psounis, and C. S. Raghavendra, "Spray and wait: an efficient routing scheme for intermittently connected mobile networks," in *Proceedings of the ACM SIGCOMM Workshop on Delay-Tolerant Networking (WDTN '05)*, pp. 252–259, Philadelphia, Pa, USA, 2005.

[35] M. McNett and G. M. Voelker, *UCSD Wireless Topology Discovery Project [EB/OL]*, 2013, http://www.sysnet.ucsd.edu/wtd/wtd.html.

[36] V. D. Le, H. Scholten, P. J. M. Havinga, and H. Ngo, "Location-based data dissemination with human mobility using online density estimation," in *Proceedings of the IEEE 11th Consumer Communications & Networking Conference (CCNC '14)*, pp. 450–457, Las Vegas, Nev, USA, January 2014.

[37] P. A. Lindgren and A. Droia, "Probabilistic routing protocol for intermittently connected networks," 2006, https://tools.ietf.org/html/draft-irtf-dtnrg-prophet-02.

[38] J. Lee and B. K. Szymanski, "Auctions as a dynamic pricing mechanism for E-services," in *Service Enterprise Integration*, C. Hsu, Ed., pp. 131–156, Kluwer, 2006.