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Bargain-based Stimulation Mechanism for Selfish Mobile Nodes in Participatory Sensing Network

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Abstract—**This paper focuses on the Participatory Sensing Network (PSN) that consists of selfish participants stimulated by certain reward programs. We propose a bargain-based mechanism to encourage cooperative message trading among the selfish nodes to maximize their rewards. We state the necessary condition for feasible message transactions in a theorem. We model message transaction as a two-person cooperative game, and we apply Nash Theorem to obtain optimal solution which is fair and Pareto optimal. We also present a greedy algorithm to reach the optimal solution. The effectiveness of the bargain-based stimulation mechanism is studied by extensive simulations based on real mobility traces.**

I. Introduction

This work centers on the Participatory Sensing Network (PSN), which consists of mobile devices to enable public and professional users to gather, analyze and share local knowledge [1]. PSN can be broadly applied in urban and civil planning, public health and epidemiology, environmental protection and natural resource management. Several well-known sensing tasks of PSN are described in [2]. Among them, the Neighborhood Walkability task aims at addressing pedestrian and bicycle safety by gathering data about neighborhood sidewalk hazards like racks, gaps, and impediments; the PEIR task collects environmental data including carbon dioxide emissions for global warming studies and health impact evaluations; the Diet Sense task keeps track of individual dietary patterns and helps to identify causes for chronic diseases.

The participants in PSN can be either voluntary or stimulated by certain reward programs. We focus on the latter in this research. More specifically, we assume the nodes are selfish and behave rationally. They collect and deliver data for the sensing tasks only if they are paid. They do not forward messages of irrelevant tasks or other nodes without justifiable reasons. At the same time, every node is rational, never wasting its resources to attack other nodes in the network. We also assume that nodes, though selfish, do not cheat; or alternatively, tamper-proof hardware is adopted to prevent cheating. The objective of this work is to design an efficient scheme for selfish nodes to maximize their reward. As to be discussed later, a stimulation mechanism promoting nodal cooperation is vital to achieve both higher gain for individual nodes and better overall network performance.

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A. Network Architecture

The underlying network architecture of PSN varies depending on its applications. A wide range of devices and communication systems (such as Bluetooth, Zigbee, Wifi, WiMAX, cell phone, and satellite) can be employed for the transmission of sensed data. Without loss of generality, we consider an abstract network model as outlined below:

- A PSN consists of mobile sensors and sinks. Low power radio (such as Bluetooth and Zigbee) is employed for communication among the nodes. Due to the short radio communication range and the nodal mobility, the connectivity of PSN is low and intermittent, like the delay-tolerant network (DTN). Upon receiving their interested data, the sinks can safely deliver them to end users.
- A PSN can support various sensing tasks. Each sensing task consists of a sink node and multiple mobile nodes.
- Each task has a unique message type, and its sink node is identified by this message type. One mobile node (possibly integrated with multiple sensing units) can participate in multiple sensing tasks simultaneously.
- When a sensor node generates a data message, the message has two information fields in its header: the message type and the message sequence number.
- When a mobile node meets a sink node, the latter accepts messages stored by the former given the following two conditions are satisfied: the message type matches the sink's task, and the message sequence number indicates that this message has not been received before.
- If a sink node accepts a message from a mobile node, the sink node rewards the mobile node with one credit unit. The mobile node that delivers the message to the sink is the only beneficiary of the reward, even it is not the message generator.
- The mobile node has limited buffer size. We assume all messages have approximately the same size.
- Transmission of a message costs one unit of energy. During its participation in PSN, the mobile node can recharge its battery from a variety of sources, such as solar or kinetic energies, at certain charging rate.

B. Related Work and Challenges

Let us first review the available stimulation schemes in the literatures. In general, there are two types of stimulation schemes for selfish ad hoc networks, reputation-based [3]

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and credit-based [4]. In the reputation-based scheme, each node is associated with a reputation that reflects its degree of cooperation (i.e., how much the node help relay packets for other nodes). The routing path is chosen according the reputation. Credit-based scheme is further divided into two approaches: packet purse and packet trade, depending on who is paying credits for packet forwarding. In packet purse approach, the source node determines a routing path and initializes each packet with sufficient credits that will be used to pay the intermediate nodes along the path. In the packet trade approach, a packet is valuable goods. The receiver pays credit to the sender of the data packet in each hop-by-hop transmission until the packet reaches its destination, the final buyer of the data.

However, none of the above stimulation schemes work in PSN, a DTN-like network. Due to the intermittent connection, it is unrealistic for a node to monitor reputations of its neighbor nodes, as required in reputation-based scheme. It is also difficult for the source node to estimate the number of intermediate nodes involved in delivering a packet and accordingly the needed credits, as required in the packet purse approach, because the end-to-end path does not exist herein. On the other hand, the packet trade approach seems suitable for PSN, because it is based on local information between the sender and the receiver in each hop-by-hop transmission, without monitoring the reputation of other nodes or estimating the path length. However, it may fail in PSN because the intermediate nodes cannot accurately determine the value of the data packets. This is due to the unique packet duplication in DTN-like networks, which is worth further elaboration. In a typical store-and-forward network, the packets are deleted from the buffer after they are transmitted to the next hop successfully. In DTN, however, since the end-to-end routing path is not available, the sender can hardly predict if the packet can eventually reach the destination, even it is successfully transmitted to the next node. Therefore, the sender usually still keeps a copy of the data which is potentially valuable after its transmission. As a result, multiple copies of the data are created and stored by different nodes in the network. Note that, however, the sink node only rewards the mobile node who delivers the packet first. So a node that pays credit for acquiring a packet may not be paid by the final buyer (or the sink), if this packet is delivered by another node to the sink. Clearly, it is nontrivial for the two trading nodes to determine the fair price of the messaged being traded.

Besides stimulation schemes for ad hoc networks, a barter-based scheme has been proposed to encourage cooperation among selfish nodes in DTN [5], where a stationary source node broadcasts messages without repetition. Each mobile node wants to receive from the source node its owns set of interested messages called primary message, and it can also receive from the source node other sets of messages called secondary message. If a node misses any primary message from the source node, it can barter its secondary messages for primary messages with an encountered node, provided that these two nodes have complementary sets of primary and secondary message. However, [5] only considers downlink broadcasting scenario in DTN, instead of the more common scenario of transmissions from various mobile nodes to one or multiple sink nodes. Moreover, it does not address multiple sensing tasks in PSN.

In summary, the unique network architecture of PSN makes the development of its stimulation schemes a very special, interesting, and challenging problem, calling for overhaul of the existing solutions for selfish ad hoc networks and DTN's.

C. Contributions

Inspired by the packet trade scheme [4] for ad hoc networks and the barter-based scheme for DTN's [5], we propose a bargain-based stimulation mechanism for PSN. To our best knowledge, this is the first paper addressing stimulation scheme for PSN.

Similar to the packet trade scheme, credit is adopted for stimulating cooperation. Nevertheless, our bargain-based scheme differs from the packet trade scheme in that message exchange between intermediate nodes does not involve credit exchange. Instead, a game theory model is developed to allow intermediate nodes to first assess the value of data message and then make transaction decisions based on the assessment.

Similar to the barter-based scheme, our bargain-based approach lets intermediate nodes exchange messages. They differ in the following aspects. First, the bargain-based approach considers mobiles nodes delivering data to the sink nodes in PSN instead of downlink broadcasting. Second, bargain-based message exchange reduces the projected value of the exchanged message, while barter-based message exchange does not. Third, the two nodes involved in message exchange have conflicting interests in bargain-based scheme but not in barter-based scheme.

The main contributions of this paper include

1) a bargain-based stimulation mechanism for selfish mobile nodes in PSN,
2) a theorem to provide necessary condition for feasible transaction of messages,
3) the formulation of the bargain process as a two-person cooperative game, whose solution is found by using the Nash Theorem, and
4) a greedy algorithm that allows mobile nodes to reach the optimal Nash Solution.

The rest of the paper is organized as follows. Sec. II introduces preliminaries and Sec. III proposes bargain-based stimulation scheme. Sec. IV presents the game model and the greedy algorithm. Sec. V discusses simulation results. Finally, Sec. VI concludes the paper.

II. Preliminaries

In this section, we introduce the preliminaries to support our proposed bargain-based stimulation scheme.

A. Contact Probability with Sink Node

Let $\mathcal{P}_i(r)$ denote node i's contact probability with the sink node of message type r. $\mathcal{P}_i(r)$ is initialized to zero, and updated at every contact with sink or at fixed time interval Δ, whichever comes first. The update function is as below.

$$\mathcal{P}_i(r) = \begin{cases} \alpha[\mathcal{P}_i(r)] + (1-\alpha), & \textit{at contact time} \\ \alpha[\mathcal{P}_i(r)], & \textit{no contact in } \Delta, \end{cases} \quad (1)$$

where $\mathcal{P}_i(r)$ and $[\mathcal{P}_i(r)]$ are values after and before update, respectively; α is the history factor with range $0 \leq \alpha \leq 1$.

B. Message Appraisal

Each message has a *message appraisal*, which measures the value of this message (that may be one of multiple copies of the same original data message). Assume node i has a message of type r and sequence number m. Let $\mathcal{A}_i^m(r)$ denote its message appraisal, which ranges from 0 to 1 and indicates the probability that nodes except i have not delivered any copy of this message m to the sink node r. When a message is generated, its initial message appraisal is set to 1. If two nodes i and j meet and they agree to send message m of type r from i to j, two copies of the message will be created and kept by nodes i and j, respectively. Their message appraisals are determined as follows:

$$\begin{cases} \mathcal{A}_i^m(r) = [\mathcal{A}_i^m(r)](1-\mathcal{P}_j(r)) & \textit{sender} \\ \mathcal{A}_j^m(r) = [\mathcal{A}_i^m(r)](1-\mathcal{P}_i(r)) & \textit{receiver}, \end{cases} \quad (2)$$

where $\mathcal{A}_i^m(r)$ and $\mathcal{A}_j^m(r)$ are the updated appraisal of message m in node i and j, respectively; $[\mathcal{A}_i^m(r)]$ is the message appraisal in node i before sending message m to node j; $\mathcal{P}_i(r)$ and $\mathcal{P}_j(r)$ are the contact probabilities of node i and j, respectively, as defined in Sec. II-A. Clearly, when more copies of a message exist, the value of each copy decreases.

C. Expected Credit Reward

Expected credit reward, denoted by $\mathcal{R}_i^m(r)$, is used by node i to anticipate the reward of trading message m of type r with encountered node. The reward is equal to the probability of node i delivers message m to the sink node r, since one delivered message leads to one credit reward from the sink node. To receive the gain, node i must first meet sink node r, whose probability is defined by $\mathcal{P}_i(r)$; then node i must make sure that all other nodes have not delivered message m yet, whose probability is defined by message m's appraisal $\mathcal{A}_i^m(r)$. Thus we have $\mathcal{R}_i^m(r)$ defined below as the product of contact probability and message appraisal:

$$\mathcal{R}_i^m(r) = \mathcal{A}_i^m(r) \times \mathcal{P}_i(r). \quad (3)$$

Similarly, the expected reward before message exchange $[\mathcal{R}_i^m(r)] = [\mathcal{A}_i^m(r)] \times \mathcal{P}_i(r)$. Notice that $0 \leq \mathcal{R}_i^m(r) \leq 1$.

D. Utility Function

Assume at time t, node i meets node j and needs to decide whether or not to exchange messages with node j. Due to its selfish nature, node i wants to maximize its own expected credit reward should message exchange happen. The utility function used by node i in decision making is as below:

$$\begin{aligned} \max \quad & \mathcal{S}_i = \sum_{r=1}^{R} \Big(\sum_{m \in \phi(r)} \mathcal{R}_i^m(r) - \sum_{m \in \psi(r)} \mathcal{R}_i^m(r) \Big), \\ w.r.t. \quad & 0 \leq l \leq \mathcal{E}_i(t), \end{aligned} \quad (4)$$

where $\mathcal{S}_i$ is the utility function of node i if message exchange happens, whose value is called utility gain; R is the total number of message types; $\phi(r)$ and $\psi(r)$ are sets of type r messages after and before exchange, respectively; l is the number of messages sent by node i; $\mathcal{E}_i(t)$ is the total energy of node i at time t before exchange. Since sending one message consumes one unit energy, we have $0 \leq l \leq \mathcal{E}_i(t)$ as energy constraint. $\mathcal{E}_i(t)$ updates as: $\mathcal{E}_i(t+\delta) = \mathcal{E}_i(t) - l + \mathcal{Z} \times \delta$, where δ is time interval for next exchange, $\mathcal{E}_i(t+\delta)$ is node i's energy at time $t+\delta$ before exchange; $\mathcal{Z}$ is energy charging rate. The initial energy of each node is $\mathcal{E}_0$.

III. Bargain-based Stimulation Mechanism

A. Overview of Proposed Stimulation Mechanism

When two nodes i and j meet at time t, a stimulation mechanism starts so as to promote cooperation that benefits both of them. The steps of the stimulation mechanism reflect how nodes interact with each other, as described below.

1) Both nodes generate their complete message lists, denoted by $\widehat{\mathcal{L}}_i$ and $\widehat{\mathcal{L}}_j$, respectively, which includes every message's type, sequence number, and appraisal.
2) Node i and j exchange control information, including $\widehat{\mathcal{L}}_i$, $\widehat{\mathcal{L}}_j$, $\mathcal{E}_i(t)$, $\mathcal{E}_j(t)$, $\mathcal{P}_i(r)$, $\mathcal{P}_j(r)$, and buffer availability information. The involved energy consumption is neglected since control information has small size.
3) Nodes i creates its candidate message list $\widetilde{\mathcal{L}}_i$ that it wants from node j, by removing node i and j's common messages from node j's complete message list, i.e., $\widetilde{\mathcal{L}}_i = \widehat{\mathcal{L}}_j - (\widehat{\mathcal{L}}_i \bigcap \widehat{\mathcal{L}}_j)$. Similarly, node j creates its candidate message list, i.e., $\widetilde{\mathcal{L}}_j = \widehat{\mathcal{L}}_i - (\widehat{\mathcal{L}}_i \bigcap \widehat{\mathcal{L}}_j)$. *Optional action:* node i removes messages of type r from $\widetilde{\mathcal{L}}_i$ if $\mathcal{P}_i(r) < \mathcal{P}_j(r)$; similarly node j removes messages of type r from $\widetilde{\mathcal{L}}_j$ if $\mathcal{P}_j(r) < \mathcal{P}_i(r)$.
4) Nodes i and j bargain which messages should be traded, based on the exchanged control information and $\widetilde{\mathcal{L}}_i$ and $\widetilde{\mathcal{L}}_j$. Bargain process is formulated as a two-person cooperative game and Nash Theorem is applied to reach optimal solution, yielding two final message lists that nodes i and j decide to exchange, denoted by $\mathcal{L}_i$ and $\mathcal{L}_j$. Clearly, $\mathcal{L}_i \subseteq \widetilde{\mathcal{L}}_i$, $\mathcal{L}_j \subseteq \widetilde{\mathcal{L}}_j$, $\|\mathcal{L}_i\| = \|\mathcal{L}_j\|$. Details of the bargain process are provided in Sec. IV.
5) Nodes i and j exchange messages, pair by pair in $\mathcal{L}_i$ and $\mathcal{L}_j$, if $\|\mathcal{L}_i\| \neq 0, \|\mathcal{L}_j\| \neq 0$.

If the optional action in Step 3 is taken, then nodes i and j are more conservative in message exchange, since they remove from candidate lists those messages that the peer node has a higher contact probability. Therefore, we name it conservative scheme; or otherwise aggressive scheme.

To summarize the stimulation mechanism, each mobile node goes from complete message list to candidate list and then to final list. Message exchange results in a win-win solution by increasing both nodes' expected credit rewards, and it promotes cooperation among selfish nodes.

B. Necessary Condition for Feasible Transaction

As discussed above, the transaction of a pair of messages between two encountered nodes is feasible only if both nodes can increase their expected credit rewards. We study the necessary conditions for feasible transaction and state the results in Theorem 1 and Lemma 1 as follows.

Theorem 1. ***Necessary Condition for Feasible Transaction****. Node i has a type r message, and node j has a type s message. If both nodes i and j find it beneficial to exchange this message pair, then $\mathcal{P}_i(r) + \mathcal{P}_j(s) < 1$ must be true.*

Lemma 1. ***Necessary Condition for At Least One Feasible Transaction between Two Nodes****. If there is at least one feasible transaction between nodes i and j, then $\min_{r \in T} \mathcal{P}_i(r) + \min_{s \in T} \mathcal{P}_j(s) < 1$ must be true, where T is the set of all message types.*

The readers are referred to Appendix for the proofs of Theorem 1 and Lemma 1. Here we give an intuitive explanation. A message transaction is a double-edged sword in the sense that it involves the exchange of a pair of messages, and receiving a message will bring credit in the expected reward, while the giving-away of a message will bring debit in the expected reward. If a transaction is feasible, the credit must outweigh the debit for both nodes, which leads to $\mathcal{P}_i(r) + \mathcal{P}_j(s) < 1$. In other words, if $\mathcal{P}_i(r) + \mathcal{P}_j(s) > 1$, the credit must be less than the debit for at least one node, which results in infeasible transaction. This result indicates that two nodes with high probabilities to deliver data are less likely to cooperate. For example, assume $\mathcal{P}_i(r)$ has a high value. When a type r message from node i is given to node j, node j has to compete with node i to deliver this message to sink node, in order to receive reward for delivering this message. Since node i already has a high probability to deliver this message by itself indicated by a high-valued $\mathcal{P}_i(r)$, therefore, node j's expected reward, proportional to $1 - \mathcal{P}_i(r)$, will be low. Since node j is selfish, it will be reluctant to cooperate with node i in this case. As a result, a node's high contact probability with sink discourages other node's willingness to cooperate.

IV. Game Theory Model for Bargain Process

In this section, we focus on the bargain process (i.e., Step 4 of Sec. III-A). We formulate it as a two-person cooperative game and introduce a greedy algorithm to derive the optimal Nash Solution.

A. Two-Person Cooperative Games

The two-person cooperative games model was proposed by John Forbes Nash in [6]. The two persons in the game are rational and selfish. Being rational means that they will not act maliciously and hurt each other's interest deliberately, and being selfish means that each person has his own objective to achieve. The rationality puts down the foundation for cooperation, while the selfishness can be an incentive or an impediment for cooperation, depending on whether the cooperation brings benefit or harm to the players. The two persons have different objectives and their interests can conflict with each other. To cope with conflict interests, the two-person cooperative game allows players to reach a binding agreement. In comparison, non-cooperative game does not allow binding agreement between players. Given the selfish nature of the two persons, the binding agreement they reach must promote the interests of both persons. In summary, a two-person cooperative game consists of two rational and selfish players that cooperate with each other but have conflict interests, thus the binding agreement they reach must benefit both persons.

In PSN, two nodes encounter and start to bargain which messages should be exchanged. Nodes are rational and willing to cooperate. Nodes are selfish, and each node has its own interest, that is to maximize its utility function defined in Equation 4. When a node tries to maximize its utility function, it may hurt the interest of the other node, since receiving a message from the other node decreases the other node's utility gain although increases its own utility gain. Thus whenever a node wants a message from the other node, it has to trade one message of its own for the desired message. When nodes cooperate in message exchange, they have conflicting interests, and the final agreement must do good to both nodes. Based on the above observations, we conclude that nodes' bargain process matches the characteristics of a two-person cooperative game, and we can model the action of each node from game theory's perspective.

B. Nash Solution

Theorem 2. ***Nash Theorem [6]:*** *The solution for two-person cooperative game, which satisfies four axioms: invariance, symmetry, independence and Pareto optimality, is given by*

$$(\hat{s_1}, \hat{s_2}) = \arg \max_{(s_1, s_2) \in \mathcal{S}} (s_1 - d_1) \times (s_2 - d_2), \qquad (5)$$

where $(\hat{s_1}, \hat{s_2})$ is the optimal solution, also called Nash Solution; $\hat{s_1}$ and $\hat{s_2}$ are the utility gain of person 1 and 2 in Nash Solution, respectively; s_1 and s_2 are the utility gain of person 1 and 2, respectively; (s_1, s_2) forms utility gain space $\mathcal{S}$; (d_1, d_2) is the status quo point in space $\mathcal{S}$, usually defined as the utility gain of no cooperation; $(s_1 - d_1) \times (s_2 - d_2)$ is called Nash product.

What Nash Theorem [6] says is that, for two-person cooperative game, the solution (s_1, s_2) that maximizes Nash product $(s_1 - d_1)(s_2 - d_2)$ is optimal. An intuitive interpretation of Nash Solution is provided by Frederik Zeuthen [7]. Zeuthen's paper envisions a two-player bargain process divided into multiple rounds. $d = (d_1, d_2)$ is the status quo point. At the beginning of each round, player 1's proposal is $\mathcal{S}^1 = (s_1^1, s_2^1)$, while player 2's proposal is $\mathcal{S}^2 = (s_1^2, s_2^2)$. Assume $\frac{(s_1^1 - s_1^2)}{(s_1^1 - d_1)} < \frac{(s_2^2 - s_2^1)}{(s_2^2 - d_2)}$, then player 1 need to make a concession from its proposal so that the relationship in the inequality is reversed. It can be shown that $\frac{(s_1^1 - s_1^2)}{(s_1^1 - d_1)} < \frac{(s_2^2 - s_2^1)}{(s_2^2 - d_2)}$ is equivalent to $(s_1^1 - d_1)(s_2^1 - d_2) < (s_1^2 - d_1)(s_2^2 - d_2)$, and notice that $(s_1^1 - d_1)(s_2^1 - d_2)$ is player 1's Nash product. That means in each round, the player with a smaller Nash product makes a concession and increases its own Nash product. In the next round, the other player's Nash product becomes the smaller one, and the other player also makes a concession and increases his Nash product. Eventually, the two players will converge to the Nash Solution that maximizes Nash product given in Theorem 2. Expression $\frac{(s_1^1-s_1^2)}{(s_1^1-d_1)}$ can be viewed as player 1's tolerant degree for conflict, since the numerator is the difference between player 1's proposal and player 2's, and the denominator serves as a normalized factor. The less the value of $\frac{(s_1^1-s_1^2)}{(s_1^1-d_1)}$, the happier player 1 is with the offer, thus the less tolerant player 1 is with the possible bargain outcome of no deal. That is why in each round the player with smaller tolerant degree for conflict concedes and brings a new proposal to solve the conflict. In bargain process, the two players protect their own interests and at the same time deal with their conflict through compromises, hence the final Nash Solution is Pareto optimal and fair to both players.

C. Greedy Algorithm for Game Solution

We apply Nash Theorem to the bargain process to derive the optimal solution $\arg\max_{(s_i,s_j)} s_i \times s_j$, where s_i and s_j are utility functions defined in Equation 4. The status quo point (d_i, d_j) is $(0, 0)$. Note that, Nash Theorem points out what the optimal solution is, but does not show how to reach the optimal solution. We need to develop an algorithm to find out $\mathcal{L}_i$ and $\mathcal{L}_j$, the final lists of exchanged messages that maximize $s_i \times s_j$. Apparently, $\mathcal{L}_i \subseteq \widetilde{\mathcal{L}}_i$, $\mathcal{L}_j \subseteq \widetilde{\mathcal{L}}_j$. Suppose $\widetilde{\mathcal{L}}_i = \{b_1, b_2, \ldots, b_M\}$ and $\widetilde{\mathcal{L}}_j = \{a_1, a_2, \ldots, a_N\}$. A message in $\widetilde{\mathcal{L}}_i$ or $\widetilde{\mathcal{L}}_j$ has sequence number $b_m (1 \leq m \leq M)$ or $a_n (1 \leq n \leq N)$. $M = \|\widetilde{\mathcal{L}}_i\|$ is the size of $\widetilde{\mathcal{L}}_i$ and $N = \|\widetilde{\mathcal{L}}_j\|$ the size of $\widetilde{\mathcal{L}}_j$. To find out Nash Solution, a brute forth approach is to exhaust the possible messages exchange patterns and search for the pattern that maximizes $s_i \times s_j$. Define $l = \|\mathcal{L}_i\| = \|\mathcal{L}_j\|$, which is the actual number of message exchange pairs. We assume $M \leq N$ without loss of generality. Thus $0 \leq l \leq M$. Let $\mathcal{Y}$ denotes the total number of exchange patterns, $\mathcal{Y} = \sum_{l=0}^{M}(\binom{M}{l} \times \binom{N}{l}) > \sum_{l=0}^{M}\binom{M}{l} = 2^M$, where $\binom{M}{l}$ is the binomial coefficient. Since $\mathcal{Y}$ grows exponentially with M and N, it is unrealistic to adopt the brute forth manner to deplete all the possible patterns looking for Nash Solution. Therefore, we propose a greedy algorithm with polynomial time complexity to converge to the optimal Nash Solution.

The greedy algorithm divides bargain process into a finite sequence of steps, and each step corresponds to the exchange of a message pair between nodes i and j. When deciding which message pair should be selected for exchange in a step, the greedy algorithm always select the message pair that has the maximum Nash product among all candidate pairs. This selection repeats in every step until no remaining pair has positive Nash product or energy or buffer limit is met. Since in each step the Nash product is maximized, the greedy algorithm is Pareto optimal, which implies that every message pair exchange is fair and optimal among all the candidate pairs. Worthy to mention is that, we can apply Lemma 1 to determine if there is any feasible transaction at all between nodes.

TABLE I
NASH PRODUCT OF MESSAGE PAIR

	a_1	a_2	$\ldots$	a_N
b_1	$S_i^{1,1} \times S_j^{1,1}$	$S_i^{1,2} \times S_j^{2,1}$	$\ldots$	$S_i^{1,N} \times S_j^{N,1}$
b_2	$S_i^{2,1} \times S_j^{1,2}$	$S_i^{2,2} \times S_j^{2,2}$	$\ldots$	$S_i^{2,N} \times S_j^{N,2}$
$\ldots$	$\ldots$	$\ldots$	$\ldots$	$\ldots$
b_M	$S_i^{M,1} \times S_j^{1,M}$	$S_i^{M,2} \times S_j^{2,M}$	$\ldots$	$S_i^{M,N} \times S_j^{N,M}$

Here is how to calculate Nash product for each message pair. Assume message a_n and b_m are selected for exchanged. Node i's utility function will have a credit due to receiving b_m and a debit due to sending a_n, while node j's utility function will have a credit due to receiving a_n and a debit due to sending b_m. Node's utility gain equals to subtracting debit from credit, as shown in Equation 6.

$$\begin{cases} \mathcal{C}_i^{b_m} = \mathcal{R}_i^{b_m}(T^{b_m}), \quad \mathcal{D}_i^{a_n} = [\mathcal{R}_i^{a_n}(T^{a_n})] - \mathcal{R}_i^{a_n}(T^{a_n}) \\ \mathcal{S}_i^{m,n} = \mathcal{C}_i^{b_m} - \mathcal{D}_i^{a_n} \\ \mathcal{C}_j^{a_n} = \mathcal{R}_j^{a_n}(T^{a_n}), \quad \mathcal{D}_j^{b_m} = [\mathcal{R}_j^{b_m}(T^{b_m})] - \mathcal{R}_j^{b_m}(T^{b_m}) \\ \mathcal{S}_j^{n,m} = \mathcal{C}_j^{a_n} - \mathcal{D}_j^{b_m}, \end{cases} \tag{6}$$

where $\mathcal{C}, \mathcal{D}$, and $\mathcal{S}$ stand for credit, debit, and utility gain, respectively; $[\mathcal{R}]$ and $\mathcal{R}$ are credit rewards before and after message transaction, defined in Equation 3; T^{a_n} and T^{b_m} are the message types of a_n and b_m, respectively. The Nash product of the message pair a_n and b_m is $\mathcal{S}_i^{m,n} \times \mathcal{S}_j^{n,m}$, as shown in Table I, where $1 \leq m \leq M, 1 \leq n \leq N$. We can apply Theorem 1 to determine the feasibility of a message pair. If not feasible, we do not need to calculate its Nash product and thus save time in creating Table I.

Algorithm 1 Greedy Algorithm for Game Solution.

1: Set final list $\mathcal{L}_i = \mathcal{L}_j = \emptyset$ and $l = 0$;
2: In Nash product table, a_n and b_m are chosen with max positive Nash product. If fail, go to step 11;
3: **if** $(\mathcal{E}_i, \mathcal{E}_j \geq l+1)$ and $(B_i(\mathcal{S}_i^{m,n}), B_j(\mathcal{S}_j^{n,m}) \geq 1)$ **then**
4: $\quad \mathcal{L}_i = \mathcal{L}_i \bigcup b_m$;
5: $\quad \mathcal{L}_j = \mathcal{L}_j \bigcup a_n$;
6: $\quad l++$; $\mathcal{E}_i--$, and $\mathcal{E}_j--$;
7: **else**
8: $\quad$ Go to step 11;
9: **end if**
10: Remove column of a_n and row of b_m, go to step 2;
11: Terminate.

We also consider the constraint of node's buffer size. Assume each node can store $\mathcal{K}$ messages at most. Let $B_i(x)$ denote the number of messages in node i with credit value less than x. Message a_n and b_m can be exchanged only when $B_i(S_i^{m,n}) \geq 1$ and $B_j(S_j^{n,m}) \geq 1$. If node i or j's buffer is full, the message with the lowest credit reward in node i or j will be replaced to make room for the exchanged message. Two nodes run the greedy algorithm and will yield the same final lists, since inputs and algorithms are the same. The greedy algorithm is summarized in Algo. 1.

V. Simulation

Our simulations are based on real mobility traces available at CRAWDAD [8–11]. The trace data can be classified into two categories, position-based and contact-based. Position-based trace data [8, 9] record GPS positions of nodes at fixed time intervals, while the real wireless communications between nodes are not included. In contrast, contact-based trace data [10, 11] provide the time of contacts among mobile nodes, but node's position information is not available.

From game theory's perspective, each node intends to maximize its own reward, and our proposed stimulation mechanism is designed to help the node to achieve this goal. Thus a direct performance metrics of the stimulation scheme is how many rewards a node can obtain. A node's reward rate is introduced to indicate whether this node gets its desired rewards, defined as the ratio of its received rewards to the number of its generated messages. Noticing that one delivered message brings one reward credit, a node's reward rate is the same as this node's delivery rate, defined as the ratio of its delivered messages to its generated messages. We define network delivery rate as the ratio of the total number of delivered messages to the total number of generated messages in the network. Similarly, network delivery rate is also the network reward rate. Thus in the following discussions, we use delivery rate and reward rate interchangeably, at both network-wise and node-wise level.

Besides reward rate, the proposed stimulation mechanism has impact on other performance metrics, such as delay, overhead and fairness. Delay is measured by the total time delay of all delivered messages divided by the number of delivered messages. Network-wise system overhead $\mathcal{H}$ is defined as the total number of messages in the network divided by the total number of delivered messages. Node i's overhead $\mathcal{H}_i$ is defined as the total number of messages that node i has transmitted to peer nodes, divided by node i's delivered messages. Fairness is defined in Jain's Fairness Index [12] as $f(x_1, x_2, ..., x_n) = \frac{(\sum_{i=1}^{n} x_i)^2}{n \sum_{i=1}^{n} x_i^2}$, where $0 \leq f \leq 1$, n is the total number of nodes, x_i is resource consumed by node i. In PSN, $x_i = \mathcal{H}_i$. A perfectly fair environment has $x_i = x_j$ for $1 \leq i, j \leq n$, resulting in $f = 1$.

We study the performances of both aggressive and conservative schemes of our bargain-based stimulation mechanism. We also compare bargain-based schemes with direct transmission where no cooperation exists among nodes, and with a fully-cooperative scheme of DTN [13], where nodes are altruistic to forward messages. To our best knowledge, [5] is the only work for stimulating selfish nodes in DTN. However, the distinct differences in network models make it unsuitable to compare [5] and our approach, as elaborated in Sec. I-B. Simulation results are presented next, categorized by trace data.

A. Position-based Trace

Trace data of ZebraNet project [8] is used in our simulations. We assume two tasks in PSN, corresponding to two message types and two sink nodes. For example, one sink node may be used by biologist to collect data about wild animals, such as animal's body temperature, eating habit and migration route; the other sink node may be used by hydrologist to collect data about water, such as movement and distribution of rivers and swamps. Let the message types of these two sinks be 1 and 2, respectively. There are 100 nodes (zebras) randomly deployed in an area of $1km \times 1km$. Messages arrive in each node according to Poisson process with message generation rate $\lambda_1 = 0.005$ messages per minute for type 1, and $\lambda_2 = 0.005$ for type 2. Max queue size is 300. Each node has an initial energy of 100 unit with an energy recharging rate of 0.14 unit per minute. Each node's wireless radius is 60m. The positions of sink nodes are randomly chosen. We run our simulation for 10000 slots, and each slot represents 1 minute. The results are shown in Figs. 1-5.

Figs. 1-4 study the network performances. Fig. 1 compares the performances of different schemes under variable max queue size. Fig. 1(a) and Fig. 1(c) shows that fully-cooperative scheme ranks highest in reward rate and overhead, followed by bargain-based aggressive scheme, bargain-based conservative scheme, and direct transmission. The high reward rate of the fully-cooperative scheme is attributed to the fact that their nodes are altruistic to forward each other's messages voluntarily, thus the chance of a message being delivered to sink is the highest among all schemes. The accompanying side effect is that the number of messages copies (overhead) is also the highest. In contrast, nodes in direct transmission do not cooperate at all, resulting in the lowest reward rate, and the number of message copies (overhead) always being one. The performances of our proposed bargain-based schemes are between the fully-cooperative and non-cooperative schemes. Specifically, the aggressive scheme is only 3% less than fully-cooperative scheme in reward rate, while the conservative scheme is 10% less. Both bargain-based schemes are 20% ~ 30% higher than direct transmission in reward rate. This confirms the effectiveness of our stimulation mechanism, which promotes nodal cooperation and improve network throughput. Comparing conservative scheme with aggressive schemes, the former has a 7% loss in reward rate, but its overhead is 70% ~ 80% less than the latter, resulting in significant reduction of energy cost. Fig. 1(d) shows that bargain-based schemes have much better fairness than fully-cooperative scheme, and this is due to bargain process's ability of allowing each node to balance between its individual interest and its contribution to network. Without the bargain process, fully-cooperative scheme can cause a node to contribute too much to other nodes, compared to its own ability to deliver messages and receive gain. Direct transmission's fairness is omitted from the figure because it is always 1. Fig. 1(b) shows that the delay performance is in reverse relation to reward rate. This is because higher reward rate implies more message exchanges, faster delivery, and shorter delay.

Fig. 1 also shows the impact of variable max queue size on performance. Along with the increase of max queue size, both reward rate and fairness of all schemes increase. Longer size queue stores more messages in each node and increases their delivery chances. Messages dropped from queue contribute to a node's overhead and results in unfairness. When max queue size increases, direct transmission's delay increases, bargain-based schemes' delay decreases, and fully-cooperative scheme's delay fluctuates. Max queue size has two impacts on delay. The first impact is to reduce delay. For bargain-based and fully-cooperative schemes, that means more exchanged messages will reside in the queue and there are better chances to deliver them using shorter time. The second impact is to increase delay. For bargain-based and fully-cooperative schemes, that means even messages with low expected rewards can find a place in the queue, and when this message gets delivered, it already has long delay, thus increasing the average network delay. For direct transmission, that means self-generated messages can stay in the queue for a longer time before being delivered. Only the second impact applies to direct transmission, thus it has increasing trend in delay. Under our simulation parameters, the first impact dominates the second one in bargain-based schemes, thus it has decreasing trend in delay. These two impacts interact with each other in fully-cooperative scheme, thus it has fluctuating delay trend. The maximum queue size also has two impacts on overhead shown in Fig. 1(c). The first one is increased overhead due to more messages stored in longer queue, and the second one is reduced average message copies due to the increase of reward rate. In bargain-based schemes, the first impact outweighs the second one, thus it results in increasing trend of overhead. But in the fully-cooperative scheme, the second impact outweighs the first one, thus it results in decreasing trend of overhead.

Fig. 2 compares the performance of different schemes under varying energy recharging rate, denoted by $\mathcal{Z}$. As shown in Fig. 2(a), when $\mathcal{Z} < 0.02$, direct transmission is the best in reward rate; when $0.02 < \mathcal{Z} < 0.1$, bargain-based conservative scheme is the best; when $\mathcal{Z} > 0.1$, bargain-based aggressive scheme and fully-cooperative scheme are better than other. It indicates that fully-cooperative and aggressive schemes are energy-consuming, and conservative scheme is suitable for energy-constrained environment, and direct transmission applies when energy is extremely low. Fig. 2(b) indicates that delay in bargain-based and fully-cooperative schemes first increases and then remains constant. When $\mathcal{Z}$ is low, most of the delivered messages are those generated by nodes close to sink nodes, resulting in smaller delay. When $\mathcal{Z}$ increases, more messages generated by nodes further away from sink nodes can be delivered, and with longer delay. When $\mathcal{Z}$ has passed a threshold, reward rate does not increase with $\mathcal{Z}$, since energy is no longer an obstacle for message delivery. For all schemes except direct transmission, the overhead shown in Fig. 2(c) first increases with the $\mathcal{Z}$ and then remains constant. The same trend applies to fairness in Fig. 2(d).

Fig. 3 depicts the impact of number of sink nodes. We assume each sink node has a unique sensing task with a unique message type. As the number of sink nodes increases, reward rate increases slightly, while delay decreases at the cost of more overhead for all schemes except direct transmission, as indicated in Fig. 3(a), 3(b), and 3(c). The reason is that with more message types generated in each node, cooperation between nodes enhances the possibility of delivering messages to their sinks. We also notice from Fig. 3(d) that fairness increases with more sink nodes, because the chances of meeting sink nodes become higher.

Fig. 4 studies the impact of message generation rate. We define ratio $\rho = \frac{\lambda_{low}}{\lambda_{high}}$ and let the total amount of type 1 and type 2 messages comparable by having half of the nodes using λ_1 as λ_{high}, and the other half using λ_2 as λ_{high}. We can see from the four sub-figures that, reward rate, delay, overhead and fairness do not change significantly. This proves that our propose bargain-based schemes work well under different message generation rates.

Different from the above discussions on network performances, Fig. 5 examines individual node's reward rate. We define reward rate improvement as the ratio of reward rate in a scheme to the reward rate in direct transmission. Shown in Fig. 5 are the distributions of node's reward rate improvement in aggressive, conservative, and fully-cooperative scheme, respectively. Fig. 5 indicates that, compared to direct transmission, fully-cooperative scheme has more than 20% nodes experience worse perfromance, while 95% nodes enjoy more rewards under both aggressive and conservative scheme. Fig. 5 also proves the fairness of our bargain-based schemes, given that they improve not only the network-wise reward rate indicated by Figs. 1-4, but also the node-wise reward rate since the dominating majority of nodes receive more rewards.

B. *Contact-based Trace*

Trace data of Cambridge Haggle project [10] is used in our simulation. In Haggle project, mobile nodes called iMotes were distributed to 50 people attending IEEE InfoCom workshop during three days. Due to hardware failure, only 41 iMotes acquired useful data. We assume there are two tasks in PSN based on Haggle trace, with two message types and two sink nodes. One sink node may be used by sociologist to collect data about how people interact with each other, such as when and how long people meet; the other sink node may be used by nutritionist to collect data about people's diet or exercise habit. Let the message types of these two sinks be 1 and 2, with message generation rates $\lambda_1 = \lambda_2 = 0.25$ per minute. The queue size in each node is 400 messages. Each node has an initial energy of 1000 units, which is recharged at 4 units per minute. We run our simulation for 4200 slots, and each slot represents 1 minute, summing up to almost three days. We need to randomly generate the contact probabilities between iMotes and sink nodes, since there is no position information in contact-based trace. Notice that fully-cooperative scheme in [13] does not apply in contact-based trace, since it heavily depends on position information. Let $\mathcal{P}_i(1), \mathcal{P}_i(2)$ denotes node i's contact probability with sink node 1 and 2, respectively. If $\mathcal{P}_i(1)$ and $\mathcal{P}_i(2)$ are both uniformly distributed between $[0, 1]$, it is called similar contact probability. In scenario of dissimilar contact probability, half of the nodes have $\mathcal{P}_i(1)$ be uniformly distributed in $[0, 0.4]$ and $\mathcal{P}_i(2)$ in $[0.6, 1]$; while the other half have $\mathcal{P}_i(1)$ in $[0.6, 1]$

and $\mathcal{P}_i(2)$ in $[0, 0.4]$. We compare bargain-based conservative scheme with direct transmission, and study how the difference in contact probabilities affects network performances. Fig. 6(a) indicates that reward rate enhancement is 50% in scenario of dissimilar contact probability, compared to 35% enhancement in scenario of similar contact probability. Fig. 6(b) shows that the delay reduction is around 35% in scenario of dissimilar contact probability, compared to 20% under similar contact probability. Thus when nodes have complementary sets of contact probabilities, as is the case for dissimilar contact probability, bargain-based mechanism achieves more gain due to higher expected rewards. Fig. 6(c) shows that higher gain is achieved at the cost of slighly increased overhead.

VI. Conclusion

In this paper, we have proposed a novel bargain-based stimulation mechanism to encourage cooperation among selfish mobile nodes in participatory sensing networks. We have revealed the necessary condition for feasible transaction of message exchange between encountered mobile nodes. We present both conservative and aggressive schemes to enable mobile nodes to create candidate lists for message exchange. The final message exchange list is determined in a bargain process, which is formulated as a two-person cooperative game to allow the two mobile nodes to compete and compromise with each other. We have introduced optimal Nash Solution for the bargain process and conducted an algorithm analysis that shows its exponential complexity. Consequently, we have proposed a greedy algorithm to resolve the game and find out optimal solution. Through extensive simulations, we have compared our stimulation schemes with direct transmission scheme of no cooperation and with fully-cooperative stimulation scheme. The results show that our bargain-based stimulation schemes are fair and have comparable performance with fully-cooperative scheme under less overhead. As far as we know, this is the first work that proposes stimulation mechanism for participatory sensing networks (PSN) and applies game theory model to solve bargain process in PSN.

Appendix

Proof of Theorem 1 and Lemma 1.

Proof: Assume node i has a message of type r with sequence number m, and node j has a message of type s with sequence number n. If node i approves the message exchange transaction with node j, then this equation must hold:

$$\mathcal{R}_i^n(s) > [\mathcal{R}_i^m(r)] - \mathcal{R}_i^m(r), \tag{7}$$

since the left side of Equation 7 is the increase in expected reward by receiving a copy of message n from node j, and the right side is the loss in reward by sharing a copy of message m to node j. Plug $\mathcal{R}_i^n(s)$, $\mathcal{R}_i^m(r)$, $[\mathcal{R}_i^m(r)]$ from Equation 2 and 3 into Equation 7, we have:

$$[\mathcal{A}_j^n(s)]\times(1-\mathcal{P}_j(s))\times\mathcal{P}_i(s) > [\mathcal{A}_i^m(r)]\times\mathcal{P}_j(r)\times\mathcal{P}_i(r). \tag{8}$$

Similarly, we have the following for node j:

$$[\mathcal{A}_i^m(r)]\times(1-\mathcal{P}_i(r))\times\mathcal{P}_j(r) > [\mathcal{A}_j^n(s)]\times\mathcal{P}_i(s)\times\mathcal{P}_j(s). \tag{9}$$

A manipulation of Equations 8 and 9 yields:

$$\frac{\mathcal{P}_i(s)\times\mathcal{P}_j(s)}{(1-\mathcal{P}_i(r))\times\mathcal{P}_j(r)} < \frac{[\mathcal{A}_i^m(r)]}{[\mathcal{A}_j^n(s)]} < \frac{(1-\mathcal{P}_j(s))\times\mathcal{P}_i(s)}{\mathcal{P}_i(r)\times\mathcal{P}_j(r)}. \tag{10}$$

Remove the item in the middle and simplify it, we have:

$$\mathcal{P}_i(r) + \mathcal{P}_j(s) < 1, \tag{11}$$

which proves Theorem 1. The proof of Lemma 1 comes from Theorem 1 naturally. We can see that in order to have at least one feasible transaction between nodes i and j, the minimum of $\mathcal{P}_i(r)$ and $\mathcal{P}_j(s)$ among the set T of all message types must satisfy Equation 11, i.e.,

$$\min(\mathcal{P}_i(r), r\in T) + \min(\mathcal{P}_j(s), s\in T) < 1. \tag{12}$$

■

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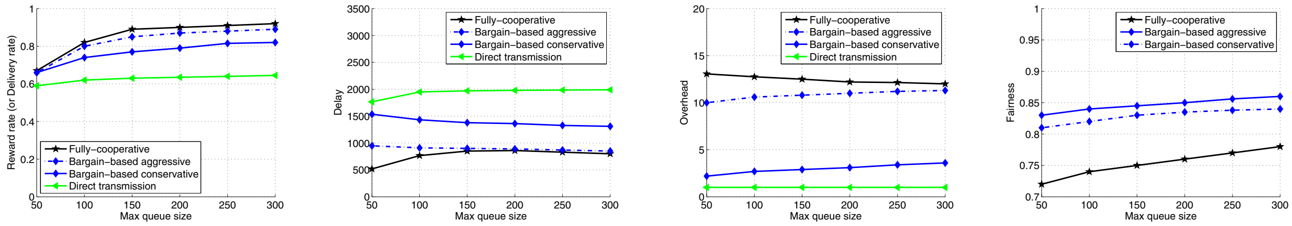
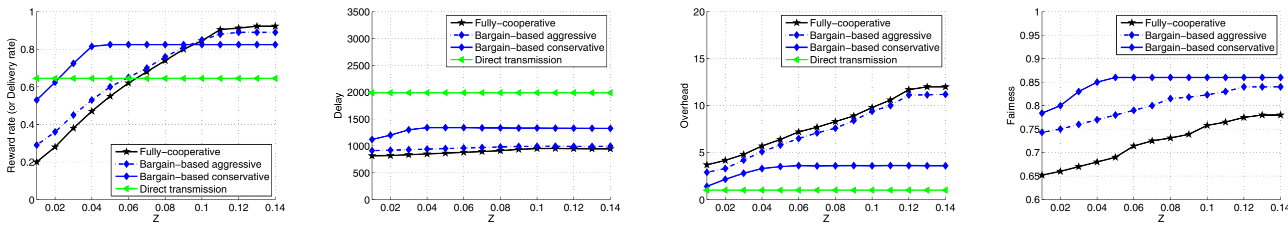


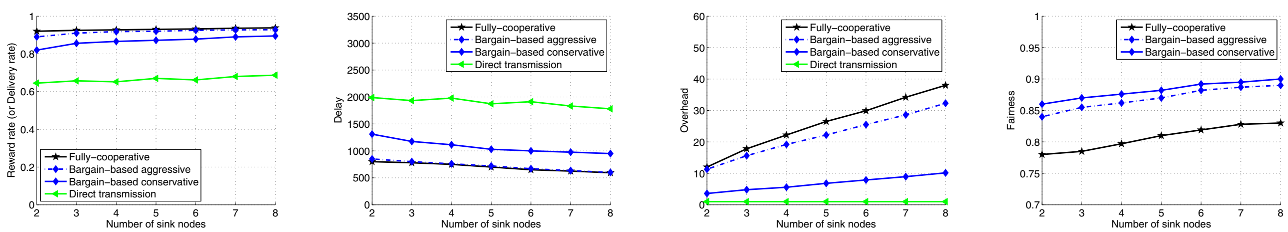
(a) Reward rate. (b) Delay. (c) Overhead. (d) Fairness.

Fig. 1. Variation of the queue size in position-based trace.



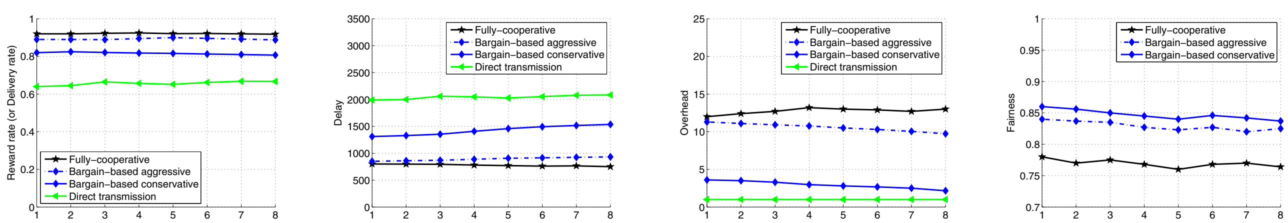
(a) Reward rate. (b) Delay. (c) Overhead. (d) Fairness.

Fig. 2. Variation of the energy recharging rate (Z) in position-based trace.



(a) Reward rate. (b) Delay. (c) Overhead. (d) Fairness.

Fig. 3. Variation of the number of sink nodes in position-based trace.



(a) Reward rate. (b) Delay. (c) Overhead. (d) Fairness.

Fig. 4. Variation of the ratio of message generation rates (ρ) in position-based trace.

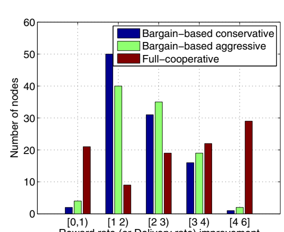
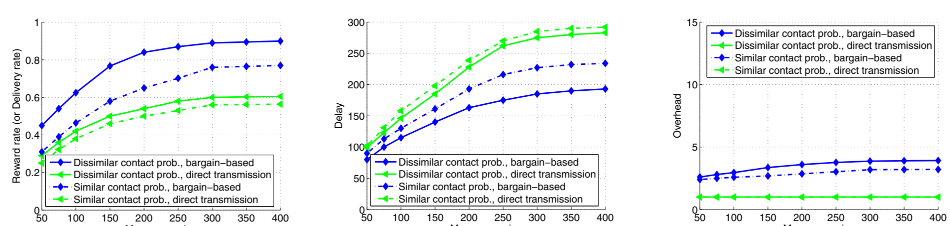


Fig. 5. Reward rate improvement



(a) Reward rate. (b) Delay. (c) Overhead.

Fig. 6. Variation of the queue size in contact-based trace.