Social-Aware Data Dissemination via Opportunistic Device-to-Device Communications

(Invited Paper)

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***Abstract*—Device-to-device (D2D) communications provide a promising paradigm for data dissemination with low resource cost and high energy efficiency. In this paper, we propose a three-phase approach for D2D data dissemination, which exploits social-awareness and addresses users' incentive constraints via moneyless mechanisms. The proposed approach includes one phase of seed selection and two subsequent phases of data forwarding. First, we build a social-physical graph and partition it into communities based on edge-betweenness, and then select one seed for each community according to vertex-closeness. In the subsequent two data forwarding phases, we propose new mechanisms for message selection and cooperation pairing which take into account both altruistic and selfish behaviors of users. The theoretical analysis proves truthfulness of the message selection mechanism. Extensive simulation results further demonstrate the effectiveness of the three-phase approach.**

***Index Terms*—Data dissemination, social-awareness, incentive constraints, truthfulness, D2D communications.**

I. Introduction and Related Works

Data dissemination aims at delivering information to a group of target users in a geographical region. It has a wide range of applications, such as in disaster alert, event notification, and advertisement distribution. The mobile-to-mobile, or device-to-device (D2D) communications, provide a promising paradigm to expedite data dissemination, while offering side benefits such as traffic offloading and energy efficiency. One widely studied data dissemination approach is based on a two-phase procedure. A base station (BS) first delivers content objects to certain selective users, called *initial sources* or *seeds*. After that, the seeds propagate the objects to other users via D2D communications, and any user that receives the data further forwards the data to others resulting in an information epidemic. Considering that portable wireless devices such as smart phones and tablets are carried by people, it is essential to address and exploit the social properties of human behaviors in cooperative data dissemination.

In the literature, there have been some existing studies on social-aware data dissemination [1]–[3]. Most existing works either assume that users are completely altruistic so that they are willing to transmit messages to anyone they encounter [1], or assume that users are absolutely selfish so that they need to be incentivized to participate in the process of data dissemination [2]. In fact, a user tends to be double-faced such that he/she is selfish to strangers but altruistic to the people with social ties such as family members, friends, colleagues, *etc*. Therefore, users' altruism and selfishness should be jointly exploited for effective data forwarding.

Based on these insights, in this paper, we propose a three-phase approach for social-aware data dissemination, which fuses the social network and mobile network for initial seed selection, and exploits users' altruism and selfishness for subsequent data forwarding. Specifically, Phase I selects seeds based on a social-physical graph model, which characterizes users' social relationships and transmission opportunities via D2D communications. Then, Phase II and Phase III follow with data forwarding to accommodate users' altruistic and selfish incentive constraints, respectively. In Phase II, data forwarding only takes place among socially connected users and a truthful moneyless mechanism is proposed for message selection. In Phase III, the BS intervenes and activates data forwarding among cooperative users which are grouped by a stable matching mechanism. We prove that the message selection mechanism is truthful and demonstrate the high performance of the three-phase approach with extensive simulations.

The remainder of this paper is organized as follows. Section II gives the system model for social-aware data dissemination via D2D communications. In Section III, we introduce the proposed three-phase approach and analyze the relevant properties. In Section IV, we evaluate the performance of our mechanisms and conclude this paper in Section V.

II. System Model

In this paper, we consider a data dissemination scenario depicted in Fig. 1, where a BS is requested to disseminate a sequence of m messages, M, to a set of n users, N, in an area. Assume that each user $i \in N$ has a heterogeneous preference toward a message $k \in M$, quantified by a normalized valuation (*i.e.*, utility) v_{ik} $(0 \leq v_{ik} \leq 1)$. The BS first chooses a subset of users $D \subset N$ as seeds and directly transmits the messages

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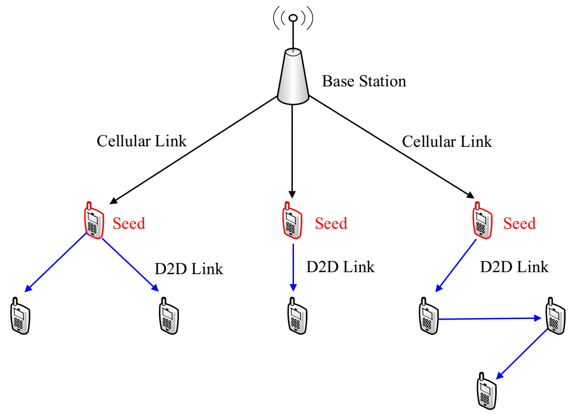

Fig. 1. Data dissemination scenario.

to them, and then the seeds and any receiving user further forward the data to others via D2D communications.

A. Social Graph Model

Here, we specify our system model from both the social and physical perspectives. First, a social graph $G_0(N, E)$ is used to model the social ties among the nodes in N, where an edge $e = (i, j) \in E$ represents that nodes i and j are socially connected via social relationships among family members, friends, colleagues, *etc*. Note that the social graph is unweighted and undirected.

B. Physical Network Model

The physical network supporting data dissemination needs to be characterized by the communication and contact processes among nodes. While the communication feasibility depends on the D2D links between any two nodes, the contact process directly varies with user mobility. Considering a target data rate, we take the time to transmit a message at this rate as one time slot τ. Then, we say that two nodes encounter each other, or are in contact, when their physical distance and D2D channel conditions can support the target data rate. For each pair of nodes i and j, their contact process alternates between encounters and inter-contacts. Referring to previous studies on real contact traces [4], we assume that the *inter-contact interval*, up to a characteristic time in the order of half a day, follows a power-law tail, which can be modeled by a Weibull or Pareto distribution. The *contact duration* is modeled by a uniform distribution [5]. The probability that nodes i and j have at least one encounter within a time frame T is termed as *contact probability* and denoted by p_{ij}.

C. Social-Physical Graph Model

Coupling the social graph G_0 and the physical network model, we have a *weighted* and undirected social-physical graph G, which inherits the node set and edge set from G_0 and further labels each edge $e = (i, j) \in E$ by a length metric

$$\text{length}(e) = \log \frac{1}{p_{ij}}. \tag{1}$$

In social network analysis, *betweenness* and *closeness* are two classic centrality measures which can identify the most influential vertices or edges in a weighted or unweighted, undirected or directed graph. Here, we consider *edge-betweenness*:

$$\text{betweenness}(e) = \sum_{s,d \in N, e \in E} \frac{\sigma_{sd}(e)}{\sigma_{sd}} \tag{2}$$

where σ_{sd} is the number of *shortest* paths from node s to node d, and $\sigma_{sd}(e)$ is the number of those *shortest* paths that pass through edge e. Given the length metric in (1), we can see that the total length of a path from node s to node d is

$$\text{length}(P) = \log \frac{1}{\prod_{e=(i,j)\in P} p_{ij}}. \tag{3}$$

In addition, we consider closeness of a vertex based on *harmonic centrality*, defined by

$$\text{closeness}(s) = \sum_{s,d \in N, s \neq d} \frac{1}{d_{sd}} \tag{4}$$

where d_{sd} is the length of the shortest path(s) (*i.e.*, the distance) from node s to node d. This closeness definition actually measures the speed of spreading information sequentially from node s to all other nodes.

III. Social-Aware Data Dissemination with Incentive Constraints

As data forwarding via D2D communications costs non-negligible bandwidth, energy, and computing resources, self-interested users should be incentivized to contribute to data spreading. Many existing studies focus on monetary incentives that involve transfer of money to compensate a forwarding node for its cost of resources. In contrast, moneyless incentives are often used in the environments where monetary compensation is difficult or prohibited. The existence of social trust between two socially connected users can justify their willingness to disseminate data to each other via D2D links when falling within the communication range. Thus, social trust can be regarded as one type of moneyless incentives, which is termed *social incentive* in the following. Moneyless incentives have been considered in cooperative communications, where a relay node helping a source-destination pair can be allocated a higher priority for channel access [6,7]. We refer to this form of moneyless incentives with exchange of resources as *cooperative incentive*. Compared to monetary mechanisms with the payment leverage, it is more challenging for a moneyless mechanism to ensure truthfulness.

To accommodate the incentive constraint, we consider a three-phase approach, which further splits data forwarding into two phases, namely, data forwarding among socially connected users, and data forwarding among cooperative users. The two phases of data forwarding exploit social incentive and cooperative incentive, respectively.

A. Phase I: Initial Seed Selection

Based on the definitions of the social-physical graph G and edge-betweenness, we can use the Girvan-Newman algorithm [8] to partition the social-physical graph into c communities. The key idea of the Girvan-Newman algorithm is to remove

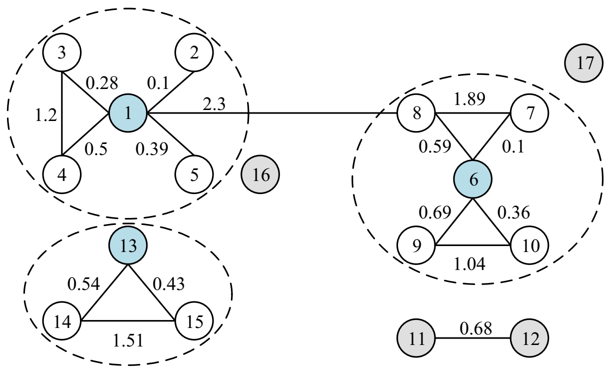

Fig. 2. Partitions of social-physical graph for community formation and seed selection. Here, three nodes (1, 6, and 13) are selected for three reasonably large communities. Nodes (11, 12, 16, and 17) are not connected to any seed and have to leverage cooperative means to receive messages in dissemination.

the edge of the highest betweenness (break a tie randomly), recalculate the betweenness of remaining edges, and repeat until there are c connected components that are "reasonably" large (*e.g.*, of a size not less than 3) corresponding to c communities. The nodes within each community are more strongly connected than those in the rest of the communities. Then, according to vertex-closeness, the node of the highest closeness in each community is selected as a seed. Here, the calculation of closeness depends on the local community structure instead of the original social-physical graph. Note that the number of seeds can be limited by adjusting the minimum size of communities.

B. Phase II: Data Forwarding Among Socially Connected Users

To improve energy efficiency, we assume that each node is only periodically activated for dissemination according to certain schedule. Specifically, an active ego node sends a catalog of available messages in possession to its socially connected nodes (for simplicity, generally referred to as "friends" in the following) within D2D communication range. Each receiving friend node returns a list of message IDs it is missing. Suppose that the ego node is subject to an energy constraint and only able to send at most g messages in one dissemination period. The ego node then needs to decide the messages it will forward to its friends. This problem can be abstracted as a bipartite graph in Fig. 3. Here, an edge between a friend node u_i and a potential message m_k indicates that node u_i is interested in message m_k and has a valuation v_{u_i,m_k} toward this message according to its preference.

This message selection problem involves two key issues. First, the ego node intends to maximize the total utility of its friends with its restricted energy, referred to as an *efficiency* requirement. Second, we need to address the strategic behavior of the receiving nodes. Since the ego node is socially connected to all receiving nodes, the social trust in between can justify the altruism of the ego node toward the receiving nodes. According to the *strong triadic closure* [9] property of social networks, if node A is connected to nodes B and C with *strong*

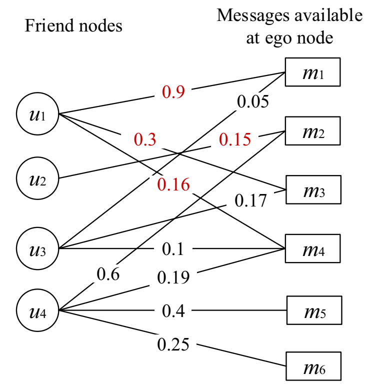

Fig. 3. Message selection modeled by a bipartite graph.

ties, it is likely that B and C are also connected for reasons such as opportunity, trusting, and incentive. Nonetheless, the ego node may have *weak ties* and violate the triadic closure property, which implies a lack of social trust among the receiving nodes. A receiving node can lie about its private preference toward the messages to maximize its own payoff. Therefore, we require a *truthful* mechanism which incentivizes the receiving nodes to report their true preferences.

As in [10], we assume that all possible values, v_{ik}'s, are known a priori or verifiable, but the edges in the bipartite graph are private. This turns the private information held by each node on the left into $\delta_{ik} = \{0, 1\}$ for each present edge. Accordingly, we propose a greedy algorithm in Alg. 1. The key idea is to scan the edges according to a non-increasing order of all known valuations v_{ik}'s and select the messages incident to the present edges. This procedure continues until all messages are selected or the maximum allowed number is reached. Next, we prove that Alg. 1 gives a truthful mechanism.

Theorem 1. *The mechanism based on Alg. 1 is truthful.*

Proof. To prove truthfulness, we consider an arbitrary friend node u_i, which reports an edge set $\hat{L}_i$. It is easily seen that $\hat{L}_i \subseteq L_i$, where L_i denotes u_i's true edges. This is because an edge $e = (i, k) \notin L_i$ indicates that u_i does not need message m_k and receiving such a message if it is selected eventually costs unnecessary energy without any real gain. Therefore, u_i has no incentive to report nonexisting edges.

On the other hand, suppose that u_i intends to improve its utility by hiding some edges in L_i. Since there is no competition when an ego node has sufficient capacity to multicast all interested messages, we focus on the case when the number of selected messages is $g' \triangleq \min\{g, m'\}$. Let $S = \{m_{\alpha_1}, ..., m_{\alpha_{g'}}\}$ denote the selected messages with u_i's truthful report which are sorted in a non-increasing order of the maximum values incident on these messages. Notice that this is also the order that these messages are selected by Alg. 1. Similarly, we denote the selected messages with u_i's untruthful report by $\hat{S} = \{m_{\beta_1}, ..., m_{\beta_{g'}}\}$. Filtering out the unique messages in S and $\hat{S}$, we can pair these two subsets of messages one by one in the order defined above.

Here, we notice one important observation which is key

Algorithm 1 A truthful approximate mechanism for message selection.

Input: N, M, $L = \{(u_i, m_k) : \delta_{ik} = 1, u_i \in N, m_k \in M\}$, $\{v_{ik} : u_i \in N, m_k \in M\}$, g

Output: $S \subseteq M = \{m_k : x_k = 1, 1 \leq k \leq m\}$, where $x_k \in \{0, 1\}$

$x_k = 0, \forall 1 \leq k \leq m$ // Initialize message selection
$S \leftarrow \varnothing$
$m' \leftarrow$ number of messages with positive total values
if $m \leq g$ **then**
  $x_k = 1$, if $\sum_{i=1}^{n} \delta_{ik} v_{ik} > 0$, $\forall 1 \leq k \leq m$
  return S
end if
$\ell \leftarrow 0$ // Track number of selected messages
Sort pairs (i, k) in a non-increasing order of v_{ik}, breaking ties consistently and arbitrarily
for all $e = (i, k) \in L$ in the above order **do**
  if $\ell = \min\{g, m'\}$ **then**
    break // No more message is available or allowed
  end if
  if $x_k = 0$ **then**
    $x_k \leftarrow 1$ // Add the newly incident message
    $S \leftarrow S \cup \{m_k\}$
    $\ell \leftarrow \ell + 1$
  end if
end for
return S

to the proof. That is, u_i is only able to change a selection from m_α to m_β if $v_{i\alpha}$ is the maximum value among all edges incident on m_α. If u_i hides such an edge, it can only affect the selection of those messages whose maximum values are less than m_α. This is because Alg. 1 selects messages in a non-increasing order of v_{ik}'s. Therefore, a hidden edge that caused the change from m_α to m_β must satisfy $v_{i\alpha} > v_{i\beta}$. The net gain of this change $(v_{i\beta} - v_{i\alpha})$ must be negative. The same reasoning can be applied to each pair of unique messages. Therefore, no positive gain motivates u_i to hide edges. $\square$

C. Phase III: Data Forwarding Among Cooperative Users

In Phase II, data forwarding periodically takes place among socially connected nodes according to each node's individual dissemination schedule. It is possible that even after time W ($W < T$), some node has not received any message as it has not had a chance to encounter its friends. On the other hand, as seen in Fig. 2, there exist some "orphan" nodes that are not connected to any seed because they are isolated or belong to small communities. If data forwarding only happened when social trust exists, these orphan nodes could not receive any message from the seeds and their connected nodes. Hence, in Phase III, we aim to enable cooperation that mutually benefits both orphan nodes and socially connected nodes.

Consider the scenario illustrated in Fig. 4. Here, u_α and u_β are two socially connected nodes, while u_γ is an orphan node. Suppose u_α wants to disseminate its available messages to a friend u_β but could not meet u_β due to their mobility patterns. If u_γ has a high chance to encounter both u_α and u_β, u_α may like to send its messages to this stranger node. If u_γ finally

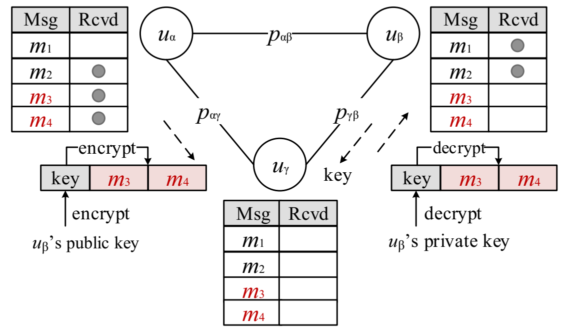

Fig. 4. Data forwarding among an orphan node u_γ and two socially connected nodes (u_α, u_β).

meets u_β and forwards its carried messages to u_β, u_γ can be granted access to these messages as a reward. To implement this cooperation idea, it is important to ensure that u_γ can only receive the reward when successfully performing the carry-and-forward task. A simple solution is that u_α encrypts the messages using a randomly generated session key y_s, and attaches the session key encrypted by the public key of u_β. Only when u_β receives the messages from u_γ will u_β pass the decrypted session key to u_γ to unlock the messages.

The cooperation pairing problem can be modeled by a bipartite graph in Fig. 5. Here, the left side is the set of orphan nodes $N' \subset N$. The right side is the set of *directional* edges, denoted by E'. Each pair of socially connected nodes (u_s, u_d) correspond to an edge $e = (u_s, u_d) \in E$ in the social-physical graph G. For each $e = (u_s, u_d) \in E$, we include two entities, $(u_s, u_d), (u_d, u_s) \in E'$, for both directions.

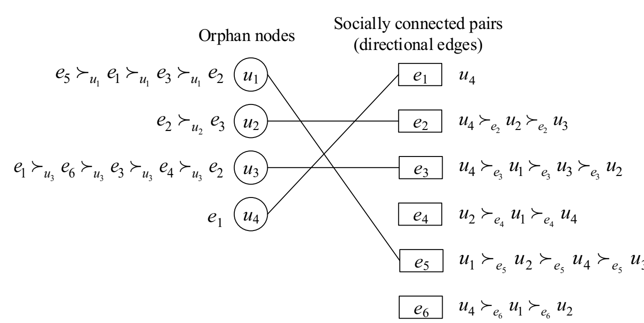

Fig. 5. A cooperation pairing example modeled as a stable matching problem with a bipartite graph.

As u_s and u_d may hold a different set of messages, denoted by M_s and M_d, respectively, an orphan node u_r thus achieves a different utility with a forwarding task from u_s to u_d or from u_d to u_s. Given a set of messages available at u_r, we say that u_r falls within the acceptable set of (u_s, u_d) and vice versa, if $M_s \cap \overline{M}_r \cap \overline{M}_d \neq \varnothing$, *i.e.*, u_s contains at least one message that is commonly interested to u_r and u_d. Specifically, u_r's *expected* valuation toward (u_s, u_d) is defined by

$$\overline{v}_{u_r}|(u_s, u_d) = p_{sr} \cdot p_{rd} \sum_{m_k \in M_s \cap \overline{M}_r \cap \overline{M}_d} v_{rk}. \tag{5}$$

As seen, u_r's valuation depends on its contact probabilities

Algorithm 2 The deferred acceptance algorithm for cooperation pairing.

Input: G, M, D

Output: $\{y_{ij} : u_i \in N', e_j \in E'\}$, where $y_{ij} \in \{0, 1\}$

$E' = \{e' = (s, d), (d, s) : e = (s, d) \in E\}$
// Transform each edge in E to two directional edges in E'
$N' \leftarrow$ nodes in N of completion ratio no more than ϑ
// Initialize set of cooperative candidate nodes
for all $u_s \in D$ **do**
  // Find nodes reachable from seeds in D
  Depth-first-search from u_s, label traversed vertices as visited
end for
$N' \leftarrow N' \cup$ unvisited vertices in N (orphan nodes)
$A_i \leftarrow \varnothing, \forall u_i \in N'$, $B_j \leftarrow \varnothing, \forall e_j \in E'$
// Sets of acceptable candidates of u_i and e_j
for all $u_i \in N'$ **do**
  // Derive valuations for preference ordering
  for all $e_j = (u_s, u_d) \in E'$ **do**
    if $M_s \cap \overline{M}_i \cap \overline{M}_d \neq \varnothing$ **then**
      $A_i \leftarrow A_i \cup \{e_j\}$, $B_j \leftarrow B_j \cup \{u_i\}$
      $\overline{v}_{ij}^{(A)} = p_{si} \cdot p_{id} \sum_{m_k \in M_s \cap \overline{M}_i \cap \overline{M}_d} v_{ik}$
      // u_i's valuation toward e_j
      $\overline{v}_{ji}^{(B)} = p_{si} \cdot p_{id} \sum_{m_k \in M_s \cap \overline{M}_i \cap \overline{M}_d} v_{dk}$
      // e_j's valuation toward u_i
    end if
  end for
end for
Return a stable matching between N' and E' by extended DAA

with u_s and u_d, and its utility from the messages that are available at u_s and demanded by both u_r and u_d. Similarly, the preference of (u_s, u_d) over u_r can be measured by

$$\overline{v}_{(u_s,u_d)}|u_r = p_{sr} \cdot p_{rd} \sum_{m_k \in M_s \cap \overline{M}_r \cap \overline{M}_d} v_{dk}. \tag{6}$$

Based on the definition in (5), each orphan node u_r has a strict preference order with respect to the directional edges in its acceptable set, denoted by E'_r. That is, $\forall\ e_\alpha = (s_\alpha, d_\alpha), e_\beta = (s_\beta, d_\beta) \in E'_r$, $e_\alpha \succ_{u_r} e_\beta$ if and only if $\overline{v}_{u_r}|(s_\alpha, d_\alpha) > \overline{v}_{u_r}|(s_\beta, d_\beta)$. Similarly, according to (6), each edge in E' has a strict preference order toward the orphan nodes in its acceptable set.

Given the set of orphan nodes N' and the set of directional edges E' representing socially connected pairs, we want to properly match N' and E' such that *both sides* are satisfied with the matching. This can be formulated as the stable matching problem. In [11], Gale and Shapley propose the deferred acceptance algorithm (DAA) to find a stable matching which is optimal to the proposing side who therefore would report their preference truthfully. The DAA can be extended for our scenario with an unequal number of agents on both sides [12] and an incomplete preference list for each agent.

Alg. 2 presents our cooperation pairing algorithm. Here, we first transform the edges in the social-physical graph into a set of directional edges, E', and identify a set of cooperative candidate nodes, including the orphan nodes and the nodes which have social connections but have received no more than ϑ (*e.g.*, 0.8) of the messages in dissemination, *i.e.*, N'. After that, we derive the valuations of each agent toward its acceptable candidates in the opposite side. The valuations are translated to the agent's preference ordering. Then, letting the candidate nodes propose, we apply the extended DAA to produce a stable matching between N' and E'.

IV. Simulation Results

A. Synthetic Datasets

To evaluate the performance of our proposed mechanisms, we conduct computer simulations over synthetic datasets, in which the number of users (n) is set to 30 and the number of messages (m) is set to 10. For comparison purpose, users' preference for a message, v_{ik}, is set to be uniformly distributed within $[0.1, 1]$. For generating the social graph of the users, we randomly select 2 users as orphans and then use a classic social network model, *the caveman model* [13], to generate the social relationships for the remaining 28 users. It is proved in [13] that social networks based on this model are very close to real ones. Here, we set the number of caves to 7, the size of each cave to 4, and the rewiring probability to 0.2.

For generating the user contact process in the physical network, we assume that users' contact duration follows a uniform distribution [5] and average encounter duration is in the range of $[3, 6]$. Users' intercontact duration is assumed to follow a heavy-tailed Weibull distribution [4] and average intercontact duration is in the range of $(5, 25]$. In order to better simulate the real scenarios, we randomly select some users in each social connected component and make these users encounter other users in the same component infrequently. Users' average periodic activation duration is set to 5 and inter-activation duration is set to 10.

B. Average Utility / Completion Ratio vs. Time

In this section, we compare our truthful mechanisms with corresponding optimal algorithms with the synthetic datasets. For Phase II, we consider the optimal algorithm, in which an ego node selects at most g messages with the highest total utility for multicast in one dissemination period. For Phase III, we use the Hungarian algorithm to obtain the optimal solution to the maximum weight bipartite matching (MWBM) problem. In the simulation, the number of seeds is set to 4 and g is set to 3. It is assumed that each message can finish transmission within one time slot. For the truthful mechanisms, the BS intervenes and performs matching when the increase of average completion ratio in two adjacent observation periods (each observation period is 20 time slots) is not larger than 0.01. Here, the average completion ratio is averaged over the completion ratios of all users, defined by the number of messages received by each user over the total number of messages. For comparison fairness, the BS intervening time for other dissemination strategies is set to be the same as that of the truthful mechanisms.

Fig. 6 and Fig. 7 show users' total utility and average completion ratio over time, respectively. As seen, high user

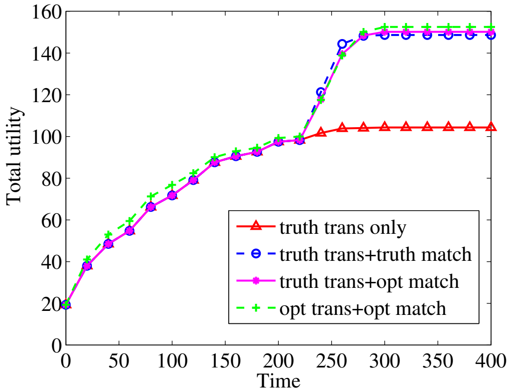

Fig. 6. Users' total utility over time.

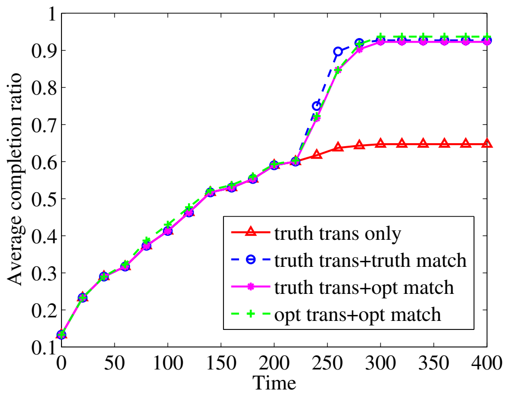

Fig. 7. Users' average completion ratio over time.

utility and competition ratio are achieved with the two phases of data forwarding. Compared with only carrying out Phase II throughout the entire process, the combination of Phase II and Phase III can effectively improve the performance. Moreover, it is observed that the performance of our truthful mechanisms is fairly close to that of the corresponding optimal algorithms.

C. *Effect of Number of Seeds*

In this section, we examine the effect of the number of seeds on our mechanisms. With the previous synthetic datasets, the number of seeds is set to 1 to 5. Similarly, the condition for the BS to intervene and perform matching is also that the increase of average completion ratio of two adjacent observation periods is not larger than 0.01. Fig. 8 shows the results of average completion ratio with different numbers of seeds. As seen, with the increase of the number of seeds, average completion ratio increases more rapidly and substantially with time during Phase II and then reaches a higher value at the end of Phase III. It is worth mentioning that when the number of seeds reaches a threshold (*e.g.*, 4 in this experiment), the influence of seed number on data dissemination becomes less evident. Specifically, when the number of seeds increases from 4 to 5, the increase of average completion ratio is not so fast or significant as that in the previous situations.

V. Conclusion

In this paper, we propose a three-phase approach for social-aware data dissemination via D2D communications. It exploits

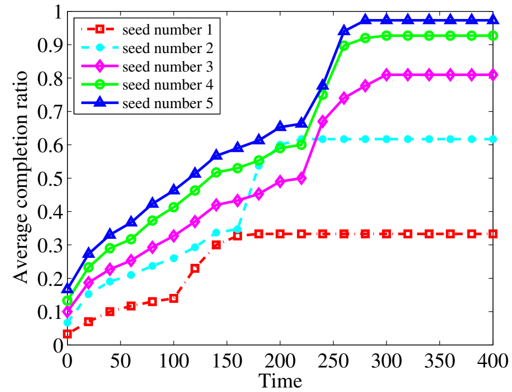

Fig. 8. Average completion ratio for different numbers of seeds.

users' social relationships in the social network and physical contacts with mobility in the physical network to improve data dissemination efficiency. Both altruistic and selfish behaviors of users are taken into account. The proposed mechanisms for message selection and cooperation pairing properly address the incentive constraints of users without resorting to monetary rewards. Thus, the proposed mechanisms are free of the hassle of payment transfer. The theoretical analysis proves that the message selection mechanism is truthful. Extensive simulation results further demonstrate the effectiveness of the three-phase approach. It is shown that the proposed mechanisms can achieve a good performance which is relatively close to that of the corresponding optimal algorithms.

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