Social-Aware Data Dissemination via Device-to-Device Communications in Wireless Networks

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Abstract

With the high penetration rate of smart mobile devices, it is appealing to exploit device-to-device (D2D) communications for data dissemination. The popularity of social networks also offers good opportunity to expedite data dissemination. In this thesis, we focus on designing schemes to perform effective social-aware data dissemination via D2D communications in wireless networks. Specifically, we aim to (1) balance between total energy consumption and transmission finishing time of data dissemination; (2) minimize total energy consumption of data dissemination while satisfying users' social incentive and power budget constraint; (3) maximize users' total preferences for messages while satisfying their incentives regarding social community; and (4) exploit social-awareness and opportunistic contacts with user mobility for data dissemination.

Firstly, we propose spanning tree based algorithms for seed selection and transmission scheduling with a single seed and multiple seeds. Secondly, we propose a coalitional graph game based approach, which iteratively derives a proper transmission graph to coordinate the data transmission of the base

station and D2D users. Thirdly, a seed selection algorithm is proposed, which models seed selection as a weighted maximum coverage problem and an approximate algorithm is proposed to solve it. Two incentive mechanisms are further proposed respectively to incentivize seeds to forward data to the remaining target users. Fourthly, we propose a three-phase approach, which consists of one phase of seed selection and two phases of data forwarding. The performance of the proposed schemes is extensively evaluated through simulations in various scenarios. The simulation results demonstrate the effectiveness of our proposed schemes for social-aware data dissemination via D2D communications in wireless networks.

To my dear parents.

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List of Abbreviations

4G	The fourth generation
5G	The fifth generation
ACK	Acknowledgement
AP	Access point
BS	Base station
DAA	Deferred acceptance algorithm
DTN	Delay tolerant network
D2D	Device-to-device
HEC	Hybrid erasure coding
IoT	Internet of Things
MAC	Medium access control
MSN	Mobile social network
MSTBD	Multiple-seed tree-based dissemination
MWBM	Maximum weight bipartite matching
M2M	Machine-to-machine
P2P	Peer-to-peer
QoS	Quality of service
SNS	Social network service
SSTBD	Single-seed tree-based dissemination
VCG	Vickrey-Clarke-Groves

Chapter 1

Introduction

In this chapter, we first introduce the motivation of social-aware data dissemination via device-to-device (D2D) communications in wireless networks. Then we discuss the challenges brought by incorporating social-awareness and D2D communications in data dissemination. After that, we present our research objectives and corresponding contributions, and give the outline of this thesis.

1.1 Motivations

Traditionally, in wireless networks, data are generally spread in the network from the node perspective through end-to-end communications, i.e., unicast, multicast and broadcast. In unicast, a node transmits data to another neighboring node. In multicast, a node sends data to a group of neighboring nodes

while in broadcast, data are transmitted from one node to all the nodes within its transmission range.

In recent years, the wireless network is migrating to an information-centric paradigm and gradually becomes dominated by data dissemination rather than merely end-to-end communications. Data dissemination in wireless networks aims at utilizing wireless communications to deliver information to a group of target users that are in need of the messages in a geographical region. Data dissemination considers the spreading of data from the network perspective by coordinating the end-to-end communications among nodes in the whole network. Data dissemination has two typical characteristics: (1) wide coverage, i.e., commonly interested messages need to be transmitted to as many target users as possible; (2) one-to-many spreading, i.e., data generally originate from one information generator and then spread to multiple information receivers.

Currently, data dissemination finds a wide range of applications in disaster alert, event notification, advertisement distribution, and multimedia content distribution, etc. For example, in disaster alert, when some disaster such as flood is going to happen, the authority can utilize base stations (BSs) to broadcast messages to mobile devices of all users in the affected areas to notify them to evacuate as soon as possible. Because of its attractive application values, the demand of data dissemination has recently experienced tremendous growth. The corresponding huge demand for network resources has led to a challenge to the network infrastructures.

Traditionally, data dissemination in wireless networks is performed by using the unicasting approach or multicasting approach, which is mainly applied in cellular networks. In these approaches, the BS either unicasts the data to each target device individually or multicasts the data once to all target devices. Nonetheless, these approaches are not energy efficient as much energy is consumed at target devices whenever data rates of long-range transmission are low [3]. Besides, such approaches may generate a large amount of data traffic, which increases the traffic load of cellular networks [4].

On the other hand, data dissemination in wireless networks can also be carried out by utilizing the broadcasting approach. This can be achieved by a fairly straightforward method, i.e., the flooding approach, which is mainly adopted in wireless sensor networks. In the flooding approach, the source node transmits messages to its neighbours and then each recipient node further broadcasts the received messages to its neighbours iteratively until the messages reach all destination nodes. However, the flooding approach is likely to consume much energy of network nodes, and generate a large number of replicate messages in the network [5].

With the rapid popularity of mobile devices such as cell phones and tablets, the communication, computing, and storage capacity of those devices enable them to become a novel kind of network resources to be utilized for data dissemination. Researchers have started to explore the potentials of leveraging the contacts among mobile devices, and perform effective data dissemination via Bluetooth or Wi-Fi, e.g., in delay tolerant networks (DTNs) [6] and

opportunistic networks [7]. These two types of networks are similar with respect to the intermittent connectivity between the nodes in the network. The DTN takes into account the tolerance of delay in data dissemination, while the opportunistic network focuses on the opportunistic contacts among nodes for data dissemination.

With the development of wireless communication techniques and proliferation of mobile devices, D2D communication has appeared as a promising technique to be utilized to expedite data dissemination. D2D communication is a key technology for the current fourth generation (4G) cellular systems and future fifth generation (5G) cellular systems. It enables two proximate devices to directly communicate with each other bypassing the BS. Due to the nature of short-range direct transmission, D2D communication has many potential advantages in term of spectrum efficiency, energy efficiency, transmission delay, and system throughput. These advantages enable D2D communication to be an effective communication method for data dissemination.

Meanwhile, in recent years, social networking services and applications have experienced explosive growth and many large-scale online social network platforms have emerged, such as Facebook, Twitter, LinkedIn, and WeChat. Studies find that the number of social media users worldwide has already been 2.46 billion in 2017, and the number is expected to reach 3.02 billion in 2021 [8]. Users' frequent daily interactions enable these platforms to exhibit resourceful information of users' social relationships that can be exploited.

Moreover, since mobile devices are carried by humans and people keep encountering and interacting with others during the process of data dissemination, people's social relationships with others provide valuable information to enable effective data dissemination.

As seen, D2D communication and social-awareness are two important paradigms for performing effective data dissemination. The benefits of D2D communication enable it to be an efficient communication technique to be utilized for data transmission between mobile devices in data dissemination. The social relationships among the holders of mobile devices are a kind of novel information dimension, which provide valuable information to facilitate data dissemination. These two aspects motive our research on social-aware data dissemination via D2D communications in wireless networks.

1.2 Challenges

Our motivated research aims to take social-awareness and D2D communication as two important paradigms to expedite data dissemination in wireless networks. In order to perform effective data dissemination, there are several critical challenges that need to be addressed.

First, as for data dissemination, due to the limited coverage capacity of the BS, the BS generally first delivers content objects to certain selective users, called seeds or initial sources, for the purposes of traffic offloading and energy saving. After that, the seeds propagate the objects to other users, and any

user that receives the data further forwards the data to others resulting in an information epidemic. In this two-phase procedure, two essential problems arise, i.e., how to properly select seeds so that they can play the maximum potential role in performing data dissemination; and how to effectively coordinate the subsequent data transmission among users. Moreover, application scenarios generally pose performance requirements to data dissemination regarding energy efficiency, finishing time, system utility, etc. The design of data dissemination schemes for these two phases should satisfy the corresponding application requirements.

Second, as for D2D communication, its interference issue in the network is a challenge to be tackled. D2D communication can be categorized into underlaying inband D2D communication, overlaying inband D2D communication, and outband D2D communication (more detailed introduction given in Section 2.1). Choosing a proper D2D communication channel model to reduce the interference is an essential problem. In addition, in the data forwarding phase, the D2D transmission links in the network should be properly scheduled so that more D2D users can transmit data simultaneously to improve system performance.

Third, as for social-awareness, since data dissemination consumes the energy and bandwidth resources of users' mobile devices, people are generally more willing to share data with friends. This users' social incentive constraint should be taken into account in data dissemination, which results in two essential problems correspondingly. On one hand, to accommodate

the incentive constraint, the scope of D2D transmission should be limited to users with social relationships. In this way, the available D2D links in the network might be reduced. Thus, a critical challenge is how to properly perform initial seed selection and subsequent transmission scheduling in such a circumstance to achieve high performance of data dissemination.

On the other hand, considering the incentive constraint, incentive schemes need to be designed to incentivize users to perform data transmission even for some strangers instead of only their friends. Monetary and moneyless incentive schemes can be designed by either rewarding users with payments, or encouraging them to cooperate and help each other mutually, respectively. Hence, we need to address another challenge on designing proper incentive schemes that incentivize users to contribute to data dissemination.

Fourth, as the holders of mobile devices may encounter each other in the daily life, both users' social ties in the social network and their mobility information in the physical network need to be jointly explored for effective data dissemination. This introduces another important problem on properly using these two kinds of information to expedite data dissemination.

1.3 Objectives and Contributions

This thesis aims to design effective schemes for social-aware data dissemination via D2D communications in wireless networks. Considering the challenges mentioned in Section 1.2, we focus on the following objectives.

Objective I: We aim to investigate energy efficiency and finishing time in data dissemination, and design an effective data dissemination scheme to balance between total energy consumption and transmission finishing time.

Objective II: We aim to incorporate D2D users' social incentive constraint and power budget constraint in data dissemination, and design an effective solution that can minimize the total energy consumption of data dissemination.

Objective III: We aim to design a preference-aware data dissemination scheme that can maximally satisfy users' preferences for messages, in which users' social relationship strengths with the members in their social communities are exploited.

Objective IV: We aim to investigate both social-awareness and opportunistic contacts with user mobility for data dissemination while taking into account users' behavior characteristics and incentives.

To achieve the above objectives, we propose several social-aware data dissemination schemes in this thesis. For Objective I, we propose a spanning tree based data dissemination scheme. In the scheme, a minimum spanning tree is used to find out the D2D links with the minimum average energy consumption so as to effectively perform seed selection. As for the transmission scheduling, the effect of parallel transmission is explored to reduce the finishing time of data dissemination.

For Objective II, we propose a coalitional graph game based data dissemination scheme. The scheme derives a transmission graph to select seeds and

coordinate data transmission of D2D users to save power consumption in data dissemination while satisfying users' social incentive and power budget constraints.

For Objective III, we propose a social community based data dissemination scheme. Specifically, a user's social relationship strengths with the members in its social community are utilized to characterize its transmission willingness and preference for these members. The scheme selects the seeds with the maximum coverage potentials regarding preferences. Two incentive mechanisms are further proposed to incentivize seeds to forward data for remaining users.

For Objective IV, we propose a three-phase approach for data dissemination, which includes one phase of seed selection and two subsequent phases of data forwarding. Phase I selects seeds based on a social-physical graph model, which exploits users' social relationships and physical contacts with mobility to improve data dissemination efficiency. The two phases of data forwarding take users' altruistic and selfish behaviors into account, and properly address their social incentive and cooperative incentive, respectively.

1.4 Outline of The Thesis

The remainder of this thesis is organized as follows. In Chapter 2, we introduce the background and related work of this thesis. We first give an introduction to the D2D communication technique and then conduct a literature

survey on traditional data dissemination and social-aware data dissemination respectively. Chapter 3 presents a spanning tree based data dissemination scheme for energy efficient and timely data dissemination within users' social incentive constraint. Chapter 4 proposes a coalitional graph game based data dissemination scheme to derive a transmission graph for energy efficient data dissemination within users' social incentive constraint and power budget constraint. Chapter 5 proposes a social community based data dissemination scheme, which exploits a user's weighted social relationships with the members in its social community. Chapter 6 presents a three-phase approach for data dissemination, which leverages social-awareness and user mobility, and addresses users' incentive constraints via moneyless mechanisms. Chapter 7 concludes this thesis and gives some potential future research directions.

Chapter 2

Background and Related Work

In this chapter, we introduce the background and the related work of this thesis. First, we start with the introduction of D2D communications. Then, we review the literature of traditional data dissemination, i.e., data dissemination in DTNs, opportunistic networks, and cellular networks. After that, we focus on social-aware data dissemination by reviewing two main areas, i.e., social-aware data dissemination approaches, and incentive schemes for social-aware data dissemination.

2.1 D2D Communication

D2D communication in cellular networks refers to the direct communication between two mobile devices without going through the BS or core network [9]. D2D communication can operate on either the cellular spectrum or unlicensed

spectrum, which are referred to as inband D2D communication and outband D2D communication respectively. In inband D2D communication, the cellular spectrum is used for both the cellular links and D2D links. Based on how the cellular spectrum is allocated between the D2D and cellular communication, inband D2D communication can be further classified into underlaying inband D2D communication and overlaying inband D2D communication.

As for the underlaying inband D2D communication, the cellular spectrum is shared between the D2D and cellular communication. The reuse of cellular spectrum can improve the spectrum efficiency of cellular networks, while it can also result in nonnegligible interference between the D2D and cellular communication. In the literature, there have been many studies on the interference management among the D2D and cellular links in underlaying inband D2D communication [10–18].

As for the overlaying inband D2D communication, dedicated cellular resources are allocated for the D2D communication. As the D2D and cellular communications occur on nonoverlapping parts of cellular spectrum, the interference from D2D communication on cellular transmission can be eliminated. Nonetheless, overlaying inband D2D communication reduces the amount of available cellular resources for cellular communication.

On the other hand, in outband D2D communication, the unlicensed spectrum is exploited for D2D links. As cellular and D2D communications utilize the licensed and unlicensed spectrum respectively, the interference between these two kinds of communication is eliminated and there is also no need

for dedicating partial cellular resources to D2D communication. However, outband D2D communication is subject to the challenges of coordinating the transmission over two different bands and requires the cellular devices to have two radio interfaces.

With short-range direct communication between devices, D2D communication offers the advantages of improving spectrum efficiency and energy efficiency, reducing transmission delay, and increasing system throughput. D2D communication was originally designed to enable multi-hop relaying in cellular networks. Gradually, it has been utilized in some other application scenarios such as machine-to-machine (M2M) communication and peer-to-peer (P2P) communication. Particularly, in recent years, with the popularity of mobile devices and the explosive growth of cellular traffic and various emerging applications, D2D communication has also been for traffic offloading, content distribution, and data dissemination.

2.2 Traditional Data Dissemination

In the literature, a large amount of early studies on data dissemination in wireless networks usually ignores users' social relationships. These works mainly focus on exploiting users' mobility and opportunistic contacts with others for data dissemination. The works on traditional data dissemination mainly concentrate on three fields, i.e., data dissemination in DTNs, opportunistic networks and cellular networks.

2.2.1 Data Dissemination in Delay-tolerant Networks and Opportunistic Networks

With the proliferation of mobile devices and the development of wireless communication techniques, opportunistic contacts among mobile devices are gradually explored for effective data dissemination, e.g., in DTNs and opportunistic networks. A common feature of these two types of networks is the intermittent connectivity between nodes. In DTNs, since the data dissemination targets at large delay tolerance, nodes can use the store-carry-and-forward approach to deliver data. In opportunistic networks, opportunistic contacts between nodes are utilized to disseminate data. Since messages are often buffered in the network waiting for a path towards the destination nodes to be available, the data dissemination in opportunistic networks is usually accompanied with the additional delivering delay for the messages [19]. Because of the similarities of the DTNs and opportunistic networks, these two terms are often utilized interchangeably. Several existing works have been proposed for data dissemination in these two types of networks, which mainly exploit the intermittent connectivity between nodes in the network.

In [20], Zeng et al. propose a mechanism for reliable bulk or stream-like data dissemination in DTNs utilizing a dynamic segmented network coding technique. The proposed mechanism consists of three phases, i.e., seeding phase, propagation phase, and acknowledgement (ACK) phase. In this mechanism, the segment sizes are adjusted according to the dynamics of the network and

a pipeline technique is utilized to accelerate the transmission of a sequence of segments of various sizes. The authors also conduct theoretical analysis and give a lower bound for the expected delivery delay of their proposed scheme. The incentive issue has also been addressed in some studies on data dissemination in DTNs. For instance, a credit-based incentive scheme is designed in [21] to stimulate collaboration among nodes in DTNs for data dissemination. In this work, it is assumed that the nodes in the network can have multiple interest types toward the data to be disseminated. When two nodes encounter, they need to decide which messages they should trade. As the nodes are assumed to be motivated by their own benefits when transmitting message to others, the trading process is modeled as a two-player cooperative game and the Nash Theorem is utilized to find an optimal solution. The proposed incentive scheme can be used to estimate the expected credit reward for a node. The credits are only rewarded to the final deliverer of the messages due to the intermittent connectivity.

In [22], Chen et al. propose a content-centric framework to facilitate data dissemination in opportunistic networks. In this work, three message scheduling algorithms are proposed to improve data delivery capacities of a hybrid erasure coding based forwarding (HEC) scheme. Then a layered multiple description coding scheme is proposed to improve data dissemination for the video transfer and web surfing applications in opportunistic networks. A semantic-based algorithm is proposed in [23] for data dissemination in opportunistic networks. It uses a data tagging approach to construct a semantic

network based on the information held by each user. Then the interaction between semantic networks is utilized to choose the information to be exchanged between the users when they encounter each other.

2.2.2 Data Dissemination in Cellular Networks

While data dissemination in DTNs and opportunistic networks depends on intermittent connectivity resulting from opportunistic contacts among devices, data dissemination in cellular networks can take good advantage of the ubiquitous infrastructure in wide areas. In general, the BS first transmits the messages to a subset of users called sources or seeds via cellular links and then relies on the short-range transmission among users using Bluetooth or Wi-Fi communication technique for further data dissemination. Many works in this area aim to optimize the completion time and energy-efficiency of data dissemination.

In [24], a framework is proposed for content dissemination in mobile cellular networks. In the framework, the BS first pushes the content to a subset of users via cellular links and then users further share the content with each other via opportunistic Wi-Fi links. The authors theoretically model and analyze the content dissemination in the scenario of a single cell and multiple cells with handover, respectively. Then an optimization framework is formulated regarding how the BS should transmit the content to users during the process of content dissemination to achieve the minimum dissemination completion time and energy cost.

The work in [25] focuses on medium access control (MAC) for data dissemination in cellular networks to coordinate the transmission of the source nodes. Formulating the data dissemination process as a noncooperative game, the authors further derive two MAC strategies, i.e., a distributed approach for adhoc networks and a coordinated approach for infrastructure networks. The two MAC strategies are analyzed mathematically in terms of energy efficiency and dissemination completion time.

2.3 Social-aware Data Dissemination

The traditional data dissemination techniques mainly focus on exploiting the mobility of users' mobile devices. In fact, as portable wireless devices such as smart phones and tablets are carried by people, the social relationships between end users are also valuable information and can be further considered to improve data dissemination. Therefore, social-aware data dissemination is proposed, which exploits end users' social features and properties to disseminate data effectively. The existing research on social-aware data dissemination in wireless networks generally fall into two main areas, i.e., social-aware data dissemination approaches and incentive schemes for social-aware data dissemination, among which many works focus on data dissemination in mobile social networks (MSNs). In this subsection, we first introduce the MSN and then introduce the existing works on social-aware data dissemination in the two corresponding areas.

2.3.1 Mobile Social Networks

An MSN is a user-centric mobile communication network that involves the social relationships of users [26]. As the MSN is a fusion of the social network and mobile communication network, it inherits and combines some features and properties of the two types of networks. In [27], experimental results show that the MSN is typically a scale-free network that exhibits small world phenomenon. In [28], it is observed that users exhibit social-related mobility pattern in MSNs. The emergence of MSNs has brought about a variety of applications such as mobile social networking services, healthcare services, location-based services, and wearable device services [26]. In addition, many aspects of human life are envisioned to be revolutionized by MSNs, such as opportunistic social interaction, disaster rescue and information sharing [29]. The architectures of MSNs can be classified into three categories, namely, the centralized architecture, distributed architecture, and hybrid architecture [26]. In the centralized architecture, a network infrastructure, such as the BSs or access points (APs), are used to exchange and deliver information between the content provider and a mobile user. In the distributed architecture, a network infrastructure does not exist and mobile users directly communicate with each other using short-range wireless technologies such as Wi-Fi and Bluetooth. As for the hybrid architecture, it can be regarded as a mixture of the above two architectures, in which a mobile user can receive data from the network infrastructure or from another mobile user.

2.3.2 Social-aware Data Dissemination Approaches

In the literature, some approaches have been proposed to facilitate social-aware data dissemination. In these approaches, social-aware data dissemination is exploited from various perspectives. The existing studies on social-aware data dissemination approaches can be roughly classified into the following groups, i.e., matching theory based, game theory based, utility-based optimization, initial source selection, and miscellaneous.

2.3.2.1 Matching Theory Based

Matching theory provides an effective tool to align the interests of two sets of agents. It has been widely used to solve various resource allocation problems in wireless networks. In the scenario of data dissemination, a set of devices that have received certain messages can cache them and further send these messages to another set of devices that still miss them through proximity-based communication techniques such as D2D communication and Bluetooth. Thus, the set of caching devices and the set of requesting devices can be viewed as the two sides of a bipartite matching problem. Then, a key issue is to properly pair the caching devices with the requesting devices to achieve certain design goal, e.g., minimal total energy consumption.

In [30], Lin et al. propose a preference-aware content dissemination scheme, which aims at optimally satisfy users' preference for the content objects. This work studies a forwarding problem of how a forwarder should optimally schedule the broadcasting of a sequence of messages to its encountered neigh-

boring nodes. This maximum-utility forwarding problem is translated into a maximum weighted bipartite matching problem and the Hungarian algorithm is then utilized to find a solution to this matching problem, which is the optimal forwarding schedule.

In [31], Ding et al. study how to minimize the transmission cost for content sharing in the wireless distributed storage system via D2D links. In this work, the spectrum sharing between cellular users and D2D links is modeled as a bipartite graph matching problem and solved by the maximum weighted matching algorithm. The derived optimal solution can minimize the total transmission cost.

2.3.2.2 Game Theory Based

Unlike the traditional data dissemination approaches reviewed in Section 2.2, social-aware data dissemination takes into account the social connections that exist among the group of target users. Due to the presence of social ties, users are more likely to choose their strategies cooperatively instead of making decisions independently and competitively. Therefore, cooperative game theory provides a good fit for social-aware data dissemination. The data dissemination process involves the receiving of data from the BS or source nodes and further data transmission toward other users. Thus, the transmission links among the nodes in the network, i.e., the coalition structure, is vital for the dissemination efficiency. In the literature, coalitional graph game and network formation game have been utilized for social-aware data dissemination

to coordinate the data transmissions among the nodes.

In [32], Sun et al. propose a social-aware approach for the fast data spreading problem over cellular networks with underlaying D2D communication. They consider a scenario in which the BS is requested to transmit similar data contents to users in an area. In their proposed solution, a social network of mobile users is first established, in which social ties among users are built up based on the probability of users' selection of the shared contents estimated by using the Bayesian model. Then, the users who have friends more than a certain threshold are selected as seeds. After that, a coalitional graph game based algorithm is proposed to coordinate the D2D transmission between users.

In [33], a network formation game is formulated to model social data offloading of selfish users via D2D communication. In the proposed game, the conditions under which the network formation process converges to a pairwise stable network are analyzed and specified. Then a practical network formation algorithm is proposed, in which users adjust their D2D sharing strategies based on their obtained payoffs in the historical period.

2.3.2.3 Utility-based Optimization

In addition to matching theory and game theory, there are also some works that model data dissemination as a utility-based optimization problem to achieve the desired objectives. Correspondingly, some algorithms are proposed in these works to find an optimal or near-optimal solution.

In [34], Ioannidis et al. study the dissemination of dynamic content over a mobile network. In this work, they first determine how the service provider should allocate its limited downlink capacity optimally to guarantee that the content at end users is as recent as possible. The optimal allocation is modeled as a social welfare maximization problem and this problem is solved by utilizing the gradient descent approach. Then they specify a condition under which the system is scalable, where the content age at users grows slowly with the increasing number of users.

In [35], Wang et al. propose a framework, called TOSS, to offload the mobile cellular traffic over MSNs by exploiting users' interaction in online social network services (SNSs) and their opportunistic sharing of data. In this framework, a subset of users, i.e., seeds, are first selected to receive the disseminated content based on their spreading impact in online SNSs and their mobility impact in offline MSNs. Then the users share the content with each other via their opportunistic contacts. The selection of seeds is modeled as an optimization problem which aims at maximizing the sum of users' access utilities and a heuristic algorithm is proposed to find the near-optimal solution. Furthermore, in [36], the authors extend the TOSS framework to a new framework called TASS, by exploiting the tags of users and contents. In TASS, an additional factor, i.e., the social similarity between two users based on tags, is included for the decision of selecting the seeds.

In [37], the authors propose ContentPlace, a social-aware data dissemination system for opportunistic networks. In ContentPlace, the relationships be-

tween a user and social communities are explored. When a user encounters another user, they exchange the information about the data objects that they carry. A user fetches the data objects it is interested in from its peer's cache. Then each user calculates a utility value for every data object in its cache and its peers' cache based on the needs of the communities it is associated with. After that, it updates the content of its cache to maximize its local utility. Different social policies are used in designing the utility function by considering the relationship between a user and community from different aspects, e.g., Most Frequently Visited and Most Likely Next.

2.3.2.4 Initial Source Selection

As seen in the previous discussions on social-aware data dissemination in Chapter I, some certain nodes, known as sources or seeds, are usually first selected to receive the dissemination content and further spread the content to other nodes. This initial step is crucial for the overall data dissemination performance. Some works have been proposed for the initial source selection problem.

In [38], Han et al. study the problem of selecting a given number of initial sources to minimize the mobile data traffic over cellular networks. The information dissemination process among users is modeled as a probabilistic dissemination model. The authors first exploit the submodularity of the information dissemination function and then propose three algorithms correspondingly for the problem of initial source selection, i.e., a greedy algorithm,

a heuristic algorithm, and a random algorithm.

A preference-aware opportunistic content dissemination scheme, named PrefCast, is proposed in [39]. PrefCast aims at utilizing users' opportunistic proximity-based communication to offload the cellular traffic from the BS while maximally satisfies users' preferences for the contents. PrefCast consists of two components, i.e., initial source-object assignment and subsequent users' forwarding scheduling. The initial source-object assignment selects the pair of the content object and the source by considering both the structure of the node community originating from the source and the resulted preferences of the nodes in the community for the content object. As for the subsequent users' forwarding scheduling, it is an extension of their previous work in [30]. In [40], Lu et al. tackle the problem of selecting a set of initial sources, through which the information can be diffused to the MSN in speed. This problem is referred to as the diffusion minimization problem and studied under a probabilistic diffusion model. The authors propose a centralized community based algorithm and a distributed set cover based algorithm for the selection of initial sources.

2.3.2.5 Miscellaneous

In addition, there are also some other works that explore social-aware data dissemination from other perspectives, which are reviewed in this section. In [41], Ioannidis et al. exploit the effect of weak ties on disseminating content updates. It is demonstrated that weak ties can play an important

role in designing users' transmission strategies to limit the bandwidth usage in the network. That is, if the users limit their contacts to others with weak ties, a favorable tradeoff between bandwidth usage and the age of users' content can be achieved. In addition, it is also shown that the importance of weak ties for the data dissemination is because of their effect on the edge expansion of the social network.

In [42], a geocommunity-based broadcast scheme is proposed for data dissemination in MSNs. This work considers the scenario in which a single superuser moves around to broadcast data to other users in the network. The authors first propose the definitions of geocommunity and geocentrality, which jointly consider users' social behaviour and geographical location. Then a semi-Markov process is used to model users' mobility on the basis of the geocommunity structure in the network. Based on the geocentrality information derived from the model, several routing algorithms are proposed to achieve the goal of minimizing completion time or maximizing dissemination ratio.

The work in [43] investigates the dissemination of real-time messages in the MSN from a ranking perspective. The MSN is modeled as a time evolving graph, which regards the dynamic network as a sequence of subgraphs that evolve over time. Then a dynamic walk counting based approach is proposed to rank the capability of the nodes for disseminating real-time messages in the network. It is noticed that the proposed ranking of node importance in spreading messages is particularly useful for mobile social applications such

as target advertisement and message spreading.

2.3.3 Incentive Schemes for Social-aware Data Dissemination

In most works reviewed in Section 2.2 on traditional data dissemination and Section 2.3.2 on social-aware data dissemination approaches, it is assumed that all users are completely cooperative. In fact, rational users can be either cooperative or selfish and they tend to be selfish when the resources that they have and can access are limited. A selfish user merely focuses on maximizing its benefit and is usually unwilling to carry and forward messages for other users. Therefore, incentive schemes are necessary to stimulate users' cooperation and attract more users to participate in the data dissemination. In the literature, there are some existing incentive schemes that aim to effectively stimulate user cooperation.

In [44], a credit-based incentive scheme is proposed to strengthen nodal cooperation for data dissemination. In this scheme, every user is initially assigned some credits. Each user estimates the ability of its neighbours to fetch messages of each interested type based on their mobile patterns. Then a user utilizes a prepay function to prepay credits to rent some users to help it fetch the desired message. If rented users deliver the messages within the given time, they will receive the credits. Based on a utility function, a user decides which other users it should rent and what kinds of messages they

should fetch. An optimization algorithm is proposed to help users obtain more interested messages while less credits are paid.

In [45], Ning et al. propose a self interest-driven incentive scheme for ad dissemination in autonomous MSNs, which are composed of a set of intermittently connected mobile nodes. In this incentive scheme, virtual cheques are proposed, which serve as prepaid credits and are included in each ad packet. When an intended receiver receives an ad packet initially from an intermediate node, the receiver authorizes the sender a digitally signed cheque, which indicates the successful delivery of the ad packet. When a node with a signed virtual cheque meets the ad provider that issues the cheque, it requests the ad provider to cash the cheque so as to obtain the credits. Both ad packets and signed virtual checks can be traded among mobile nodes separately. The interaction between two nodes is formulated as a two-player cooperative game and its solution is obtained by the Nash Bargaining Theorem.

In [46], Bigwood et al. propose a reputation-based incentive scheme, called IRONMAN, for opportunistic networks, which utilizes social network information to encourage selfish nodes to participate in the contention distribution. In IRONMAN, each node is marked by a trust score which is adjusted based on whether it forwards the received message to the encountered destination nodes in the network. If the trust score of a node is not greater than the trust threshold, that node will be detected as a selfish node. Selfish nodes are punished such that all the messages with those nodes as sources will be discarded by receiving nodes. Thereby, nodes are encouraged to behave co-

operatively so as to increase their trust scores and keep a good reputation so that their own messages are delivered by others.

Chapter 3

Efficient Spanning Tree Based Data Dissemination

As we have discussed in Chapter 1, because of the constraint of limited resources, many data dissemination schemes leverage a subset of users, i.e., seeds, to facilitate data dissemination. In these schemes, the BS first selects a subset of users as seeds and then transmits data to these selected seeds via cellular links. After that, the seeds forward the data to other users using D2D communication, and any users receiving the data can further send the messages to others via D2D links. This data dissemination approach can result in a dissemination path that originates from the BS and reaches every target user without a cycle. If we abstract the BS and each user as a node in a graph, the resulting data dissemination paths are actually a spanning tree with the BS as the root node. Since the efficiency of data

dissemination highly depends on the final data dissemination paths, it is very important to generate a proper spanning tree for data dissemination based on the requirement of applications.

In this chapter, we focus on two important application requirements of data dissemination, i.e., energy efficiency and transmission finishing time. We utilize social network information to jointly select seeds and schedule the further transmission among D2D users. As data dissemination consumes energy and bandwidth resources, people are generally more willing to share data with friends. To accommodate the incentive constraint, we limit the scope of D2D transmission to users with social ties as in [32]. A minimum spanning tree is used to find out the D2D links with minimum average energy consumption so as to effectively perform seed selection. As for the transmission scheduling, the effect of parallel transmission is also explored to reduce the finishing time of data dissemination. The simulation results show that our solution achieves a good balance between energy consumption and finishing time in the single-seed and multiple-seed scenarios. Table 3.1 lists the symbols used in this chapter.

3.1 System Model

3.1.1 Data Dissemination Model

We consider a data dissemination scenario depicted in Fig. 3.1. The BS is requested to disseminate some data to a set of n users in an area, denoted by

V. The BS first chooses a subset of those users as *seeds*, denoted by $S \subset V$, and then multicasts the data to the selected seeds at an authorized frequency channel. After that, the seeds forward the data to other users by D2D communications, while any user that receives the data can further disseminate

Table 3.1: Symbols for Chapter 3.

Symbol	**Definition**
n	Number of target users in an area for data dissemination
V	Set of target users in an area for data dissemination
S	Set of seeds
x_i	Signal transmitted from D2D user i
y_j	Received signal at D2D user j
$P_{t,i}$	Transmit power of D2D user i
h_{ij}	Channel response of link from D2D user i to D2D user j
n_j	Additive white Gaussian noise at D2D user j
ℓ	Cellular user whose uplink channel is shared with D2D underlay link from i to j
R_{ij}	Channel rate of D2D link from i to j
B_{ij}	Bandwidth of resource blocks consumed by D2D link from i to j
F	Message size
τ	Length of one time slot
K	Number of initial isolated complete graphs in the caveman model
p	Rewiring probability
G	Bidirectional graph modeling D2D communications among users with social connnections
E	Available D2D links between D2D users
e_{ij}	D2D transmission from user i to user j
$w(e_{ij})$	Transmit power for D2D communication from user i to user j
t_i	Receiving time of user i
Q	Message transmission sequence
T	Minimum spanning tree
$G^{'}$	An undirected graph converted from bidirectional graph G
G^{*}	A bidirectional graph built from bidirectional graph G based on spanning tree T
β	Weighting factor

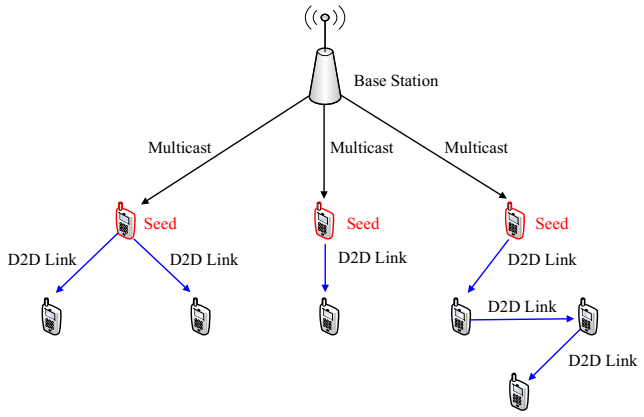


Fig. 3.1: System model.

the data to others similarly via D2D links. Our considered data dissemination model here can be applied in many real-world application scenarios where multiple-hop D2D communication chains can form among the crowd in a geographical area, e.g., disseminating live information about a match to a large number of audience filling in a stadium.

Here, we consider a D2D underlaid cellular network, where the D2D links share the uplink spectrum of regular cellular users. There are several reasons for favoring the use of uplink resources, since the uplink resources are often less utilized than the downlink resources and the BS is more powerful than the mobile devices in interference mitigation [47]. As D2D links reuse the same frequency resources with regular cellular users, this results in inevitable interference between D2D links and cellular users. In the literature, schemes on resource allocation and interference management [48–50] have been proposed to mitigate uplink interference and achieve the desirable quality of service (QoS) of D2D links and cellular users.

When the D2D underlay link from i to j shares the uplink channel of cellular user ℓ, there exists interference between D2D user j and cellular user ℓ. Then, the received signal at D2D user j can be written as

$$y_j = \sqrt{P_{t,i}} h_{ij} x_i + \sqrt{P_{t,\ell}} h_{\ell j} x_\ell + n_j \tag{3.1}$$

where x_i and x_ℓ are the signals from i and ℓ transmitted with power $P_{t,i}$ and $P_{t,\ell}$, respectively, h_{ij} and $h_{\ell j}$ are the channel responses of links from i to j and from ℓ to j, respectively, and n_j is the additive white Gaussian noise at j. The second term in (3.1) is the interference from ℓ to j. Thus, the channel rate of the D2D link from i to j is given by

$$R_{ij} = B_{ij} \cdot \log_2 \left(1 + \frac{P_{t,i} \cdot |h_{ij}|^2}{P_{t,\ell} \cdot |h_{\ell j}|^2 + |n_j|^2}\right) \tag{3.2}$$

where B_{ij} is the bandwidth of the resource blocks consumed by the D2D link from i to j.

Consider a Rayleigh fading channel model with log-distance path loss. Then, the received signal power at j, $P_{t,i}|h_{ij}|^2$, and the power of interference from cellular user ℓ, $P_{t,\ell}|h_{\ell j}|^2$, are exponentially distributed with mean $P_{t,i} d_{ij}^{-\alpha}$ and $P_{t,\ell} d_{\ell j}^{-\alpha}$ respectively, where d_{ij} is the distance between i and j, $d_{\ell j}$ is the distance between ℓ and j, and α is the path loss exponent. Here, we assume that a message of size F is transmitted in one time slot of length τ. Then, the data rate demand for the message is a constant, *i.e.*, $R_{ij} = F/\tau$. Accordingly, we can obtain the required transmit power from i to j, $P_{t,i}$.

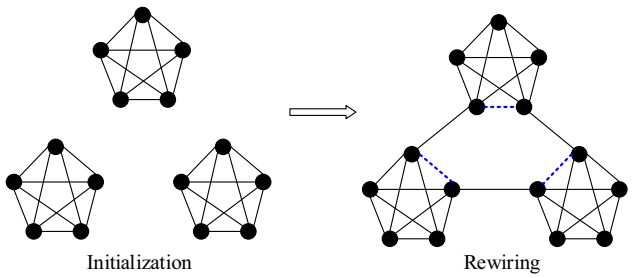


Fig. 3.2: Generation of a social network using the caveman model (adapted from [1]): (a) Initial network topology with 3 caves of size 5. (b) Generated social network after the rewiring stage.

3.1.2 Social Network Model

To accommodate user incentive constraint, we assume that D2D data dissemination only occurs between two socially connected users whose physical distance and D2D channel conditions can meet the data rate requirement. To characterize the social relationships among D2D users, we use *the caveman model* [51], a classic social network model which can generate synthetic social networks with realistic characteristics.

The caveman model starts with K isolated complete graphs, also known as *caves*, in which every vertex is adjacent to every other vertex. Then in a rewiring stage, every edge of a cave in the original network is randomly rewired by pointing to a node in another cave with probability p. The rewiring procedure intends to establish random inter-connections between individual nodes of different caves. Fig. 3.2 shows an example to generate a synthetic social network with the caveman model.

As discussed in [1], the individual nodes of one cave are closely connected,

while individual nodes of different caves are sparsely connected. That is, the generated social network is globally sparse but locally dense. Therefore, the social networks generated by the caveman model are featured with high clustering coefficients and low average path length. It has been proved in [51] that social networks based on this model are very close to real ones.

3.1.3 Design Objective

Given the system model in Section 3.1.1, we can model the D2D communications among the users with social connections as a bidirectional graph $G(V, E, w)$, where V is the set of D2D users, E denotes the available D2D links between the D2D users, and each edge is labeled by weight $w(e_{ij})$, which gives the transmit power for the D2D transmission from user i to user j. Here, we aim to design a data dissemination solution, which can properly select the seeds and schedule the D2D transmission among the D2D users so as to reduce the total energy consumption of D2D transmission and the final finishing time of data dissemination, *i.e.*,

$$\min_{E' \subseteq E} \sum_{e_{ij} \in E'} w(e_{ij}) \tag{3.3}$$

$$\min_{Q \in \mathcal{Q}} \max\{t_i\}, i \in V \tag{3.4}$$

where t_i denotes the receiving time of user i following the transmission sequence Q. Since the two performance metrics are not independent in our

scenario, it is very difficult or even impossible to minimize the total energy consumption and completion time simultaneously. Therefore, we set reducing the total energy consumption as our primary goal while achieving a balance with the transmission completion time.

3.2 Spanning Tree Based Seed Selection and Transmission Scheduling

As seen in the problem discussed in Section 3.1, it is quite complex to jointly select the initial seeds and coordinate further data dissemination so as to minimize the total energy consumption and transmission completion time. Particularly, in the wireless network with limited energy budget, it is preferable to have a lightweight approximate solution which can approach the best performance. Here, we first propose a data dissemination algorithm for the single-seed scenario and then extend it to the multiple-seed scenario.

3.2.1 Single-Seed Scenario

Alg. 1 presents a single-seed tree-based dissemination (SSTBD) algorithm for selecting one seed in the bidirectional graph $G(V, E, w)$ and scheduling the data transmission. SSTBD consists of two sub-procedures, SSA and TRA, specified in Alg. 2 and Alg. 3 respectively, which correspond to two individual stages, seed selection and transmission scheduling. For easy presentation, we

Algorithm 1: SSTBD($G(V, E, w)$).

Input: $G(V, E, w)$
Output: S, (t_1, t_2, ..., t_n)
1 $Tree_s \leftarrow$ SSA($G(V, E, w)$)
2 (t_1, t_2, ..., t_n) $\leftarrow$ TRA($Tree_s$)
3 Return $S =$ getRootNode($Tree_s$), (t_1, t_2, ..., t_n)

assume that graph G is connected. Our algorithm also works when G is not connected by regarding each connected component as an individual graph.

For the SSA algorithm, it first converts the bidirectional graph $G(V, E, w)$ into an undirected graph $G'(V, E', w')$ by combining each pair of original edges $e_{ij}, e_{ji} \in E$ into an edge $e'_{ij} \in E'$ using the geometric mean $w'(e'_{ij}) = \sqrt{w(e_{ij}) \cdot w(e_{ji})}$, which can reflect the average energy consumption of the D2D link between user i and user j. Then the minimum spanning tree T of G' is generated to find out the D2D links with the minimum average energy consumption. After that, tree T is restored to a bidirectional graph $G^*(V, E^*, w)$ by replacing edge e'_{ij} in T with the original edges e_{ij} and e_{ji} in G. Then for each node i in G^*, we build a transmission tree, $Tree_i$, which is rooted at i and spans over G^*, and obtain the total energy consumption by summing up the weights of edges in $Tree_i$. Finally, the node which achieves the minimum total energy consumption is selected as the seed. Fig. 3.3 gives an example that illustrates the above operations for choosing the seed.

The time complexity of SSA algorithm is analyzed as follows. Converting the bidirectional graph G into the undirected graph G' takes $O(|E|)$ time. Constructing the minimum spanning tree T of G' by the Kruskal's algorithm

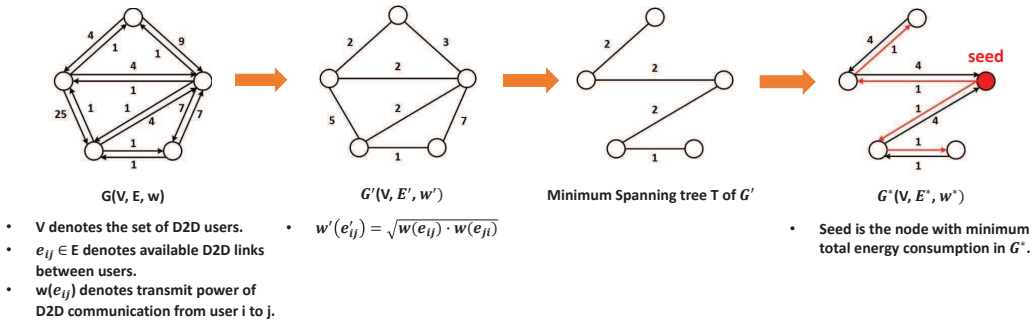
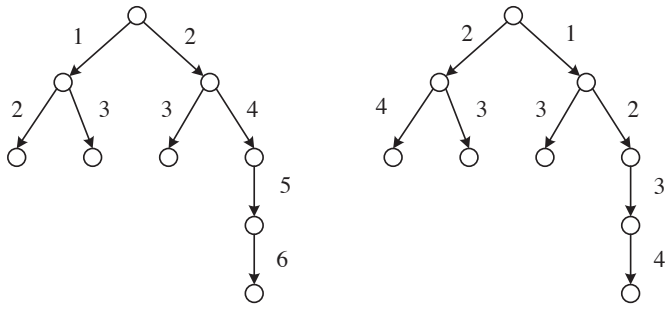


Fig. 3.3: An example for the operations of choosing a single seed.

takes $O(\frac{|E|}{2} log|V|)$ time. Generating the bidirectional graph G^* based on the tree T takes $O(|E|)$ time. Selecting the seed on the graph G^* takes $O(|V|)$ time. Thus, the overall time complexity of SSA is $O(|E|log|V|)$.



(a) Finishing time = 6 (b) Finishing time = 4

Fig. 3.4: An illustrative example on the impact of transmission order. The label on each edge is the time slot in which the transmission occurs.

As seen in Alg. 2, the seed selection is performed on the bidirectional graph $G^*(V, E^*, w)$ generated from tree T which is connected and acyclic. Once the seed is selected, the data transmission paths in G^* are determined. The transmission paths are actually a directed tree rooted at the seed, in which

Algorithm 2: SSA($G(V, E, w)$).

Input: $G(V, E, w)$
Output: $Tree_s$
$E' = \emptyset$
for $e_{ij}, e_{ji} \in E$ **do**
    $w'(e'_{ij}) = \sqrt{w(e_{ij}) \cdot w(e_{ji})}$ *// Define a new weight for each undirected edge*
    $E' = E' \cup e'_{ij}$
Define graph $G'(V, E', w')$
$T = \text{GetMinSpanTree}(G'(V, E', w'))$ *// Compute minimum spanning tree of* G'
$E^* = \emptyset$
for $e'_{ij} \in T$ **do**
    $E^* = E^* \cup e_{ij} \cup e_{ji}$ *// Replace undirected* e'_{ij} *by directional* e_{ij} *and* e_{ji}
Define graph $G^*(V, E^*, w)$
for $i \in V$ **do**
    Generate tree $Tree_i$ rooted at node i based on G^*
    $totalEnergy_i = \sum_{i,j \in T_i} w(e_{i,j})$
$s = \text{argmin}_{i \in V} totalEnergy_i$
Return $Tree_s$

a directed edge e_{ij} represents that node i transmits data to node j. The finishing time of data dissemination depends on the time order that a node transmits the data to its children in the tree. Fig. 3.4 shows an example that the finishing time is decreased when each node first transmits data to its child node in a subtree of more descendants and higher heights.

Here, we consider two important factors in determining the transmission order, *i.e.*, the number of descendants of node i in tree $Tree_s$, $descendant(i)$, and the height of the subtree rooted at that node, $height(i)$. Therefore, in

Algorithm 3: TRA($Tree_s$)

Input: $Tree_s$
Output: (t_1, t_2, ..., t_n)

```
for i ∈ Tree_s do
    N_i ← getChildNode(i)
    for n_i ∈ N_i do
        descendant(n_i) ← number of descendants of n_i
        height(n_i) ← height of subtree rooted at n_i
    maxDesc(i) = max_{n_i ∈ N_i} descendant(n_i)
    maxHeight(i) = max_{n_i ∈ N_i} height(n_i)
    for n_i ∈ N_i do
        infScore_{n_i} ← β · descendant(n_i)/maxDesc(i) + (1 − β) ·
        height(n_i)/maxHeight(i)
t_seed ← 0
for i ∈ Tree_s do
    Sort N_i into L_i in descending order of infScore_{n_i}
    for n_i ∈ N_i do
        t_{n_i} = t_i + n_i's position number in L_i
```

Alg. 3, we determine the transmission order using an influence score for each node i in G^*, which is defined as a weighted sum [52] of the two attributes $descendant(i)$ and $height(i)$, *i.e.*,

$$infScore_i = \beta \cdot descentant(i)_{norm} + (1 - \beta) \cdot height(i)_{norm}.$$

Here, $descentant(i)_{norm}$ and $height(i)_{norm}$ are the normalized values of the two attributes, while β ($0 < \beta < 1$) is a weighting factor. Thus, each node transmits the data to its children following the ranking of their influence scores.

3.2.2 Multiple-Seed Scenario

In this section, we extend Alg. 1 to the multiple-seed scenario with k seeds ($k \geq 2$). Alg. 4 gives a multiple-seed tree-based dissemination (MSTBD) algorithm. The main rationale of MSTBD is to break $(k-1)$ bidirectional edges in G to convert the original graph into k connected subgraphs and then perform single-seed selection and transmission scheduling in each subgraph using SSTBD. Intuitively, the total energy consumption can be potentially reduced by breaking edges of large weights. However, it may be detrimental to the transmission finishing time. For example, the subgraphs can be quite unbalanced such that the parallelization with multiple seeds cannot be effectively utilized to reduce the completion time. Since we intend to balance between the total energy consumption and the transmission finishing time, we use an alternative approach which breaks the edges such that the variance of the size of so generated k subgraphs is minimized. Fig. 3.5 gives an example that illustrates the MSTBD algorithm when $k = 3$.

The time complexity of MSTBD algorithm is analyzed as follows. The procedure of breaking $(k-1)$ edges such that the variance of the size of generated subgraphs is minimized takes $O(\binom{|E|}{k-1}) = O(|E|^{k-1})$ time. Applying the SSTBD algorithm in each generated subgraph takes $O(k \cdot |E|log|V|)$ time. Thus, the overall time complexity of MSTBD is $O(|E|^k)$.

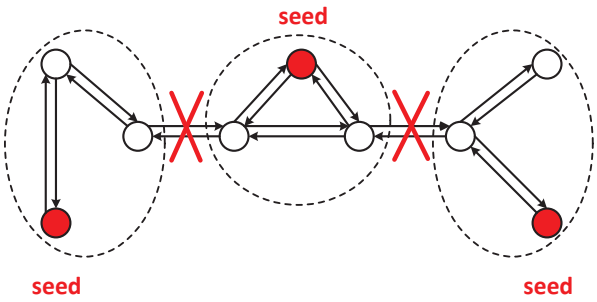


Fig. 3.5: An example that illustrates MSTBD algorithm when $k = 3$.

3.3 Simulation Results

To evaluate the performance of our proposed algorithms, we conduct computer simulations with a 200m×200m square region in which cellular users and D2D users are uniformly deployed. The number of cellular users is fixed at 150, while the number of D2D users varies in the simulations. Each D2D user is assigned an arbitrary cellular uplink channel for its D2D communications. The D2D transmission range is set to 100m. The transmit power of cellular users is set to 24dBm and the carrier bandwidth is set to 1MHz. The data rate demand for the message is set to 1MB/s. The path-loss exponent and noise variance are set to $\alpha = 1$ and $\sigma^2 = 5 \times 10^{-7}$ mW, respectively. We use the caveman model with different rewiring probabilities to generate the social relationships among D2D users.

Two reference data dissemination schemes are compared with our proposed algorithms. First, we consider a random approach, which randomly selects the seed(s), and then have each user who has received the message forward the data to an arbitrary friend who is within the D2D range but has not

Algorithm 4: MSTBD($G(V, E, w), k$)

Input: $G(V, E, w), k$
Output: $S = \{s_1, ..., s_k\}$, (t_1, t_2, ..., t_n)

$l = 0$ // *l is index of choices for breaking edges*
for $E_{k-1} \subseteq E$ **do** // *E_{k-1} is any $(k-1)$ edges in E*
  $l = l + 1$
  Generate k subgraphs $G_g^l(V_g^l, E_g^l, w_g^l)$, $1 \leq g \leq k$ by breaking edges in E_{k-1}
  $|\overline{V}^l| = \frac{1}{k}\sum_{g=1}^{k} |V_g^l|$
  $Var^l = \frac{1}{k}\sum_{g=1}^{k} (|V_g^l| - |\overline{V}^l|)^2$
$z = \text{argmin}_{1 \leq m \leq l} Var^m$
for $g = 1 : k$ **do**
  $(s_g, (t_{g_1}, ..., t_{g_{|V_g^z|}})) \leftarrow \text{SSTBD}(G_g^z(V_g^z, E_g^z, w_g^z))$
Return $S = \{s_1, ..., s_k\}$, (t_1, t_2, ..., t_n)

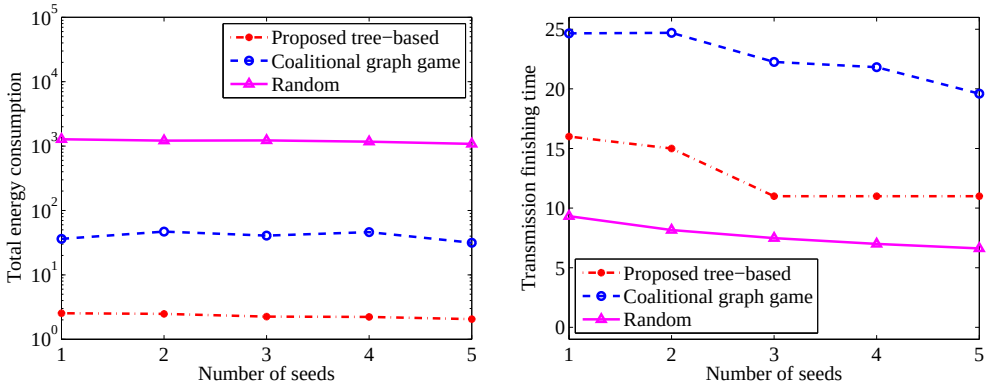
received the data. This procedure continues until all users have received the data. Second, we consider a coalitional graph game approach based on [32][1]. Here, the first k users with the largest number of friends within the D2D range are selected as seed(s). To coordinate the D2D data dissemination, a coalitional graph game is formulated to build a transmission graph $\hat{G}(V, \hat{E})$ from the initial bidirectional graph $G(V, E)$. Different from [32], we define the utility function as $U(\hat{G}) = \sum_{e_{ij} \in \hat{E}} (m_i - m_j)(w_{max} - w(e_{ij}))$, where m_i (or m_j) is a binary indicator denoting whether i (or j) has possessed the data, and w_{max} is the maximum weight of edges in E.

[1]The coalitional graph game in [32] considered here for comparison is different from the coalitional graph game approach proposed in Chapter 4 in terms of the design. The coalitional graph game approach in Chapter 4 aims to solve a different data dissemination problem with power budget constraints for D2D users.

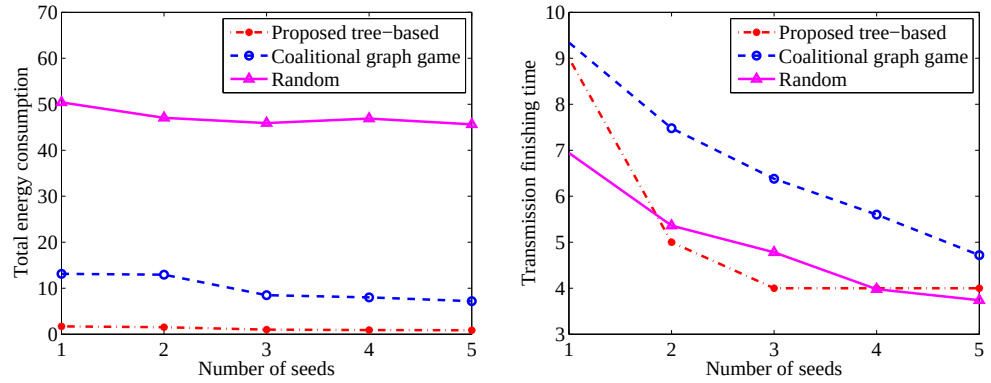
3.3.1 Effect of Network Sizes and Number of Seeds

First, we run simulations with different numbers of D2D users and seeds. The social relationships are modeled by the caveman model with two caves and a rewiring probability $p = 0.3$. The size of each cave is adapted with the number of D2D users. As the random approach and coalitional graph game based approach involve random decisions, we run the corresponding simulations for 50 times to remove the randomness effect. Fig. 3.6 shows the results of total energy consumption and finishing time for different scenarios. As seen in Fig. 3.6(a) and Fig. 3.6(c), the proposed tree-based algorithms (SSTBD and MSTBD) can effectively reduce the total energy consumption when the number of D2D users is scaled up.

Moreover, when the network size is small ($n = 20$), Fig. 3.6(b) shows that the finishing time of our solution is relatively lower than that of the coalitional graph game based approach. Though the random approach achieves the lowest finishing time, it suffers a significantly higher energy cost. In the random approach, all users who have received the message randomly transmit the data to their friends that they have not transmitted to. As a result, the number of receiving users will grow at a nearly exponential rate when the network is connected. However, the random approach has the highest energy consumption to attain the lowest finishing time. Nonetheless, when there is a large D2D user population and more than one seed, Fig. 3.6(d) shows that our solution achieves almost the lowest finishing time. This is mainly because our solution can effectively balance the energy cost and transmission



(a) $n = 20$. (b) $n = 20$.



(c) $n = 100$. (d) $n = 100$.

Fig. 3.6: Comparison of data dissemination algorithms with different network sizes and numbers of seeds.

time in MSTBD when building the subgraphs for the seeds.

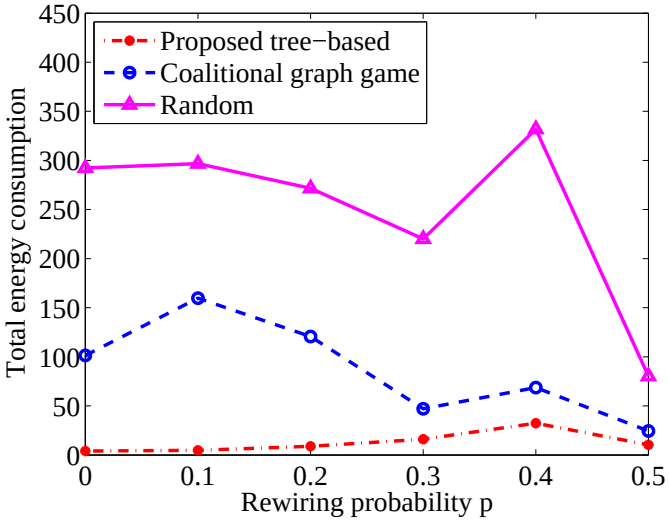
In addition, we can see that, as for different network sizes ($n = 20$ and $n = 100$), the overall system performance of our proposed approach increases with more seeds selected. When the number of seeds increases, the total energy consumption of D2D communication gradually decreases and transmission finishing time first decreases significantly and then becomes relatively stable. Nonetheless, when more seeds are chosen, the BS will consume more energy

and bandwidth resources to transmit data to seeds, and have higher overhead for coordinating the D2D transmission. Therefore, in order to determine an appropriate number of seeds, we need to achieve a balance for the tradeoff between the improvement of system performance and corresponding resource consumption and overhead of the BS.

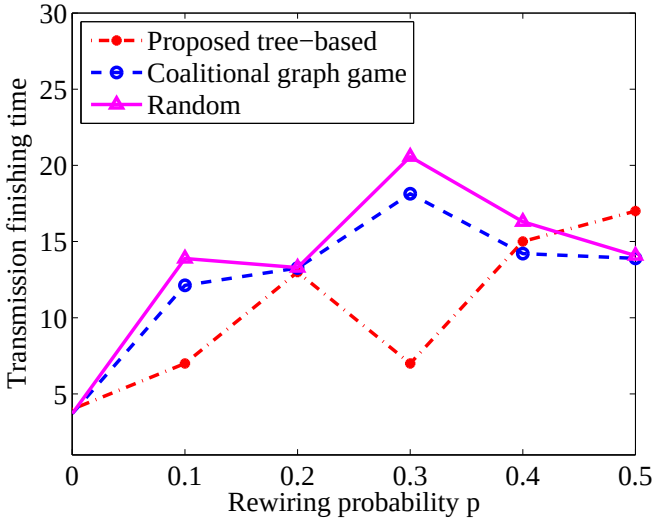
3.3.2 Effect of Social Connection Structures

Further, we test the performance of the data dissemination algorithms with different social connection structures. Here, we fix the number of D2D users to 50, the number of caves to 10, and the size of each cave to 5. Then, we change the rewiring probability p ranging from 0 to 0.5 to generate social networks of different characteristics. In particular, the number of social communities varies with the rewiring probability p. With a larger value of p, the D2D users become more densely connected in the social network and there are less isolated social communities. Based on the so generated social networks, we conduct simulations to compare the three data dissemination approaches again.

Fig. 3.7 shows the total energy consumption and finishing time with different social structures. Here, we set the number of seeds selected for each D2D cluster to 1. As seen in Fig. 3.7(a), our solution always achieves the lowest total energy consumption for different values of p. In addition, with the increase of p, the total energy consumption of our algorithm only varies slightly, while the other two schemes fluctuate dramatically. This implies that our



(a) Total energy consumption.



(b) Transmission finishing time.

Fig. 3.7: Comparison of data dissemination algorithms with different social structures.

solution is more tolerant of variations of social structures. In Fig. 3.7(b), we can see that our algorithm also effectively reduces the finishing time of data dissemination. Specifically, when the rewiring probability $p < 0.4$, the finishing time of our algorithm is the lowest among the three schemes. It is worth mentioning that the sharp drop of finishing time at $p = 0.3$ is due to the particular network topology for this case. Because the network topology is determined by the physical distance between D2D users and the rewiring probability p, this case happens to result in very balanced transmission trees of similar size for different D2D clusters. As a result, a high level of parallelization leads to quite low finishing time.

3.4 Summary

In this chapter, we have studied how to take advantage of social connections and D2D communications to achieve energy-efficient and time-efficient data dissemination. We propose novel spanning tree based algorithms for seed selection and transmission scheduling with a single seed or multiple seeds. The proposed solution can effectively balance between energy consumption and transmission finishing time via seed selection and transmission scheduling. In the simulations, we validate the effectiveness of our algorithms and compare them with two reference data dissemination schemes. The simulation results show that our solution can improve the two aspects in various scenarios with different network sizes and social structures.

Chapter 4

Coalitional Graph Game Based Data Dissemination

In Chapter 3, we propose a centralized spanning tree based scheme that handles two application requirements of data dissemination, i.e., energy efficiency and finishing time. In this chapter, we focus on two other important aspects of data dissemination, i.e., users' social incentive constraint and power budget constraint. As data dissemination consumes energy and bandwidth resources, people are generally more willing to share data with friends. Therefore, to meet users' social incentive constraint, some works limit the scope of D2D transmission to users with social ties, assuming that every user is able to disseminate data to all its friends within the D2D transmission range [32]. In fact, as portable wireless devices are battery-powered and users generally expect that their devices can operate for a long time to handle daily activi-

ties, people often set a power budget and only contribute limited power for data dissemination. Hence, we take into account both social and budget constraints of D2D users to enable more practical data dissemination. It is found that it is very difficult to obtain an optimal solution that minimizes the total power consumption of data dissemination while satisfying such constraints. Therefore, we propose a distributed approach based on coalitional graph game to approach the optimal solution. The proposed approach iteratively derives a transmission graph for data dissemination, i.e., a spanning tree, to perform seed selection and subsequent transmission scheduling. Simulations are conducted to compare the proposed approach with the optimal solution and two other schemes. The simulation results demonstrate the high performance of our approach in various scenarios with different network scales and social connections. Table 4.1 lists the symbols used in this chapter.

4.1 System Model

4.1.1 Data Dissemination Model

Here, we consider the same data dissemination scenario depicted in Fig. 3.1 of Chapter 3. The BS, b, is requested to disseminate some data to a set of n users in an area, denoted by N. The BS first chooses a subset of those users as *seeds*, denoted by $M \subset N$, and then multicasts the data to the selected seeds at an authorized frequency channel. After that, the seeds forward the data to other users by D2D communications underlaying the cellular network, while

Table 4.1: Symbols for Chapter 4.

Symbol	Definition
b	Base station
n	Number of target users in an area for data dissemination
M	Set of seeds
N	Set of target users in an area for data dissemination
x_i	Signal transmitted from D2D user i
y_j	Received signal at D2D user j
ℓ	Cellular user whose uplink channel is shared with D2D underlay link from i to j
$P_{t,i}$	Transmit power of D2D user i
h_{ij}	Channel response of link from D2D user i to D2D user j
n_j	Additive white Gaussian noise at D2D user j
B_{ij}	Bandwidth of the resource blocks consumed by D2D link from i to j
F	Message size
τ	Length of one time slot
R_{ij}	Channel rate of D2D link from i to j
γ	Transmission data rate demand for the message
f_{ij}	Indicating whether user i and user j are socially connected
K	Number of intial isolated complete graphs in the caveman model
p	Rewiring probability
V	Set of the BS and D2D users
E	links from BS to D2D users and available links between D2D users
$E^{'}$	Set of selected links for data dissemination
$w(e_{ij})$	Transmit power for transmission from node i to node j
B_i	Power budget of user i
G	A directed graph modeling transmission from BS to D2D users and D2D communications among users with social connections
G^*	A directed graph representing the result of interactions among users
d_i^{in}	In-degree of node i in graph G^*
d_i^{out}	Out-degree of node i in graph G^*
P_{max}^*	The largest power consumption of all links in graph G
(a_i, b_i, c_i)	State of node i in graph G^*. a_i is the node that node i receives data from, b_i is the node that node i transmits shared data to, and c_i records the node that has promised to transmit shared data to node i
$< a_i, b_i >$	Available strategy of node i
S_i	Strategy space of node i
S_i^*	Set of feasible strategies of node i
$U(G^*)$	Utility function with respect to transmission graph G^*

any user that receives the data can further disseminate the data to others similarly via D2D links.

We adopt the same D2D communication channel model as introduced in Section 3.1.1, where the D2D links share the uplink spectrum of cellular users. When the D2D underlay link from i to j shares the uplink channel of cellular user ℓ, there exists interference between D2D user j and cellular user ℓ. Then, the received signal at D2D user j can be written as[1]

$$y_j = \sqrt{P_{t,i}} h_{ij} x_i + \sqrt{P_{t,\ell}} h_{\ell j} x_\ell + n_j \tag{4.1}$$

where x_i and x_ℓ are the signals from i and ℓ transmitted with power $P_{t,i}$ and $P_{t,\ell}$, respectively, h_{ij} and $h_{\ell j}$ are the channel responses of links from i to j and from ℓ to j, respectively, and n_j is the additive white Gaussian noise at j. The second term in (4.1) is the interference from ℓ to j. Thus, the channel rate of the D2D link from i to j is given by[2]

$$R_{ij} = B_{ij} \cdot \log_2 \left(1 + \frac{P_{t,i} \cdot |h_{ij}|^2}{P_{t,\ell} \cdot |h_{\ell j}|^2 + |n_j|^2}\right) \tag{4.2}$$

where B_{ij} is the bandwidth of the resource blocks consumed by the D2D link from i to j. Here, we consider a Rayleigh fading channel model with log-distance path loss. In addition, we assume that a message of size F is

[1]Equation (4.1) that gives the received signal at a D2D user is the same as Equation (3.1).

[2]Equation (4.2) that gives the channel rate of a D2D link is the same as Equation (3.2).

transmitted in one time slot of length τ. Then, the data rate demand for the message is a constant, *i.e.*, $R_{ij} = F/\tau \triangleq \gamma$. Accordingly, we can obtain the required transmit power from i to j, $P_{t,i}$.

4.1.2 Social Network Model

Let f_{ij} denote whether user i and user j are socially connected. To accommodate user incentive constraint, we assume that D2D data dissemination only occurs between two users if they are socially connected, and their physical distance and D2D channel conditions can meet the data rate requirement, and the resulted power consumptions of users' devices satisfy the budget constraints. To characterize the social relationships among D2D users, we use *the caveman model*, which is the same social network model as adopted in Chapter 3. It has been proved in [51] that social networks based on this model are very close to real ones. The caveman model starts with K isolated complete graphs, also known as *caves*, in which every vertex is adjacent to every other vertex. Then in a rewiring stage, every edge of a cave in the original network is randomly rewired by pointing to a node in another cave with probability p. The rewiring procedure intends to establish random inter-connections between individual nodes of different caves.

4.1.3 Design Objective

Given the system model in Section 4.1.1, we can model the transmission from the BS to D2D users and the D2D communications among the users with social connections as a *directed* graph $G(V, E, w)$, where V is the set of the BS (b) and D2D users (N), *i.e.*, $V = \{b\} \cup N$, E denotes the links from the BS to D2D users and the available D2D links between D2D users, and each edge is labeled by weight $w(e_{ij})$, which gives the transmit power for the corresponding transmission from node i to node j. Let $E' \subseteq E$ denote the set of selected links for data dissemination, where $E' \subseteq E$ implies that each node in N only forwards data to its socially connected users. Here, we aim to design a data dissemination solution, which can properly coordinate the data transmission of the BS and D2D users so as to minimize the total power consumption of data dissemination while satisfying each user's power budget constraint, *i.e.*,

$$\min_{E' \subseteq E} \sum_{e_{ij} \in E'} w(e_{ij}) \tag{4.3}$$

$$\text{s.t.} \quad \sum_{j \in S_i} w(e_{ij}) \leq B_i, \forall i \in N \tag{4.4}$$

$$\{j : \forall e_{ij} \in E'\} = N \tag{4.5}$$

where S_i is the set of users that receive data from user i, or in other words, the head endpoints of the outgoing edges of node i in E', and B_i is the power budget of user i. Constraint (4.4) requires that the power budget of each user

be respected. Constraint (4.5) indicates that each user in N should receive the disseminated data.

4.2 Coalitional Graph Game Solution

As for problem (4.3) formulated in Section 4.1, it is essentially to construct a minimum spanning tree of the directed graph G with the BS as the root node, which satisfies the power budget constraint of each node. Correspondingly, the child nodes of the BS in the generated tree will be the seeds. In fact, it is very complex to obtain the optimal solution to this problem. A straightforward approach is to first enumerate all the spanning trees of graph G, *e.g.*, using the algorithm in [53], then find the feasible spanning trees that satisfy the node budget constraints, and last return the feasible spanning tree with the minimum total power consumption. Instead of directly applying such a costly centralized approach, we propose a distributed solution based on a coalitional graph game, which is preferable for the wireless network with limited power.

4.2.1 Design Rationale

As we have discussed, users are generally willing to share data with their friends as long as the power consumption does not exceed their limited power budgets. Hence, this forms a coalitional group among the socially connected users and the BS in the network. Moreover, in data dissemination, a user

needs to first receive data from a source node and then transmit the data to some other users. Thus, the transmission links among the nodes in the network, *i.e.*, the coalition structure, are very important. Based on these insights, we design a *coalitional graph game* for the formulated problem to coordinate the transmission among the nodes in the network.

During the process of data dissemination, the result of interactions among the nodes can be represented by a directed transmission graph $G^*(V, E^*)$, in which a directed edge $e^*_{ij} \in E^*$ indicates that there is a link to transmit data from node i to node j. Similar to [32], we assume that each user device is equipped with a single antenna. Thus, the maximum number of links from or to node i at any moment is limited to 1. Letting d_i^{in} and d_i^{out} denote the in-degree and out-degree of node i in graph G^*, we have $d_i^{\text{in}} \in \{0, 1\}$ and $d_i^{\text{out}} \in \{0, 1\}$ at any snapshot of the evolving transmission graph.

As for the coalitional graph game, an important component is the definition of utility function. Here, we define the utility function with respect to the transmission graph $G^*(V, E^*)$ as

$$U(G^*) = \sum_{e^*_{ij} \in E^*} (P^*_{\max} - P_{t,i}) \tag{4.6}$$

$$P^*_{\max} = \max_{e_{ij} \in E} \{w_{ij}\} + \epsilon \tag{4.7}$$

where $P^*_{\max}$ is the largest power consumption of all links in graph $G(V, E, w)$ plus a small constant value ϵ, and $P_{t,i}$ is the transmit power of user i to forward data to user j. This utility definition can be interpreted as follows.

At a starting point, suppose that every node $i \in N$ in the network can only receive data from a virtual source node x, which transmits data to node i with transmit power $P^*_{\max}$. Following the starting point, a node i takes allowed actions iteratively and switches to a different source under certain conditions. Accordingly, the transmission graph G^* is updated. The more the power reduced from the initial choice, the higher the utility resulting from the new transmission graph.

4.2.2 Solution Details

Given a transmission graph $G^*(V, E^*)$ in a certain iteration, the state of any node i in graph G^* is represented by (a_i, b_i, c_i), which indicates that node $i \in V$ receives data from $a_i \in V$ (the upstream node of i) and transmits shared data to $b_i \in N$ (the downstream node of i). For notation simplicity, let $a_i = i$ when $d_i^{\text{in}} = 0$ and $b_i = i$ when $d_i^{\text{out}} = 0$. In order to track the state of nodes and transmission links, we include c_i to record the node that has promised to transmit shared data to node i, *i.e.*, the actual transmission source to node i.

With a current transmission graph $G^*(V, E^*)$, we consider that node i can do nothing in an iteration or take an allowed action among the following or certain combinations:

- Offer to establish new link(s) e^*_{ij}, where $j \neq i$ and $f_{ij} = 1$ (*i.e.*, $e_{ij} \in E$), if $d_i^{\text{out}} = 0$, which *intends* to add to E^* new *outgoing* links from node

i;

- Accept to establish a new link e^*_{ji}, if $d_i^{\text{in}} = 0$ and $f_{ij} = 1$, which adds to E^* a new *incoming* link to node i; and

- Break an existing link $e^*_{ij} \in E^*$ from i to j, if $d_i^{\text{out}} = 1$.

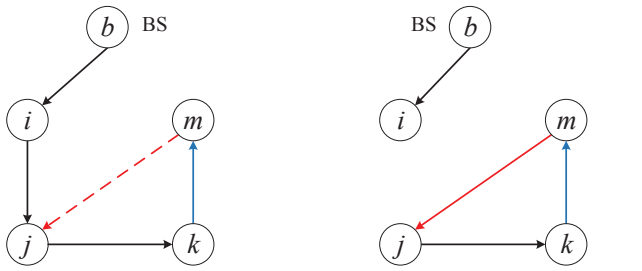
Here, the accept-link action of node i is accompanied by an offer-link action to establish a new link to each node that is socially connected with i. That is, after a node receives data from a newly established link, it will immediately request to transmit data to other nodes. Besides, the break-link action of node i for an outgoing link is combined with an offer-link action to establish a link to a different downstream node.

It is worth emphasizing that a node can transmit shared data to only one node in each round, due to the single antenna constraint. In order to explore more potential receivers, a transmitter i needs to first break its transmission link to the current receiver j to reset d_i^{out} to 0 (*i.e.*, b_i is set i), so as to offer another node a new link. Simultaneously, the state of node j is synchronized to $d_j^{\text{in}} = 0$ and $a_j = j$, so that j can accept the request from a better source. Since the break-link action is tentative for searching better options, c_i in the new state is not simultaneously reset with the break-link action but only updated when a better link is established. As seen, c_i is mainly for backtracking purpose to reconstruct the entire transmission graph. Hence, we define an *available strategy* of node i by $\langle a_i, b_i \rangle$, which indicates the immediate result relevant to node i in the new graph due to its action. Then, the strategy space of

node i is denoted by $S_i = \{s_i = \langle a_i, b_i \rangle \mid a_i \in V, b_i \in N\}$.

According to [54], an available strategy is *feasible* if and only if the utility of the new graph resulting from the strategy is not less than that of the current transmission graph. In our scenario of data dissemination, this definition is likely to result in a cycle without a valid source. Fig. 4.1 shows such an example. As seen, originally, there is a transmission path from the BS to node k, $b \to i \to j \to k$. Then, node m accepts the offer from node k and establishes the transmission link from k to m. After that, node m offers to transmit data to node j. Assuming that the transmission link from m to j consumes less power than the link from i to j, node j will choose to receive data from m instead of i. As a result, a cycle $j \to k \to m \to j$ is formed. Obviously, such a cycle without a valid source is infeasible, since none in the cycle is associated with a transmission link from the BS and thus cannot start the data dissemination. In addition to avoiding cycles, a feasible strategy also needs to respect the nodes' power budget constraints. Therefore, we extend the definition of feasible strategies as follows.

Definition 1. *An available strategy* $s_i = \langle \tilde{a}_i, \tilde{b}_i \rangle \in S_i$ *is* feasible *for user* $i \in V$ *with state* (a_i, b_i, c_i) *if and only if* $U(\tilde{G}^*) \geq U(G^*)$*, and this strategy will not lead to a cycle without a source, and the resulted power consumption of each user satisfies its corresponding budget constraint, where* $G^*(V, E^*)$ *is the current transmission graph and* $\tilde{G}^*(V, \tilde{E}^*)$ *is the consequent transmission graph following strategy* s_i*. The set of feasible strategies of node* i *is denoted by* S_i^**.*



(a) After node m accepts the transmission request from node k, it sends transmission request to node j.

(b) Assuming $P_{m,j} < P_{i,j}$, node j chooses to receive data from node m instead of i. Thus, a cycle without a source is formed.

Fig. 4.1: An illustrative example on how a cycle without a source is formed.

The most popular approach to solving a coalitional graph game is to iteratively play *myopic best-response dynamics*. In our case, a node is randomly selected in each round and plays a feasible strategy, which will not decrease the utility of the transmission graph, *i.e.*, not increase the total power consumption. Furthermore, as the game aims to gradually increase the utility and approach the optimum, the node is supposed to choose among all feasible strategies the one that maximizes the current utility. This is defined as the *local best response*, which is the feasible strategy that maximizes the utility given that the other nodes maintain their strategies [54]. Thus, the nodes in the proposed coalitional graph game keep playing their best responses unilaterally to explore more efficient transmission links for increasing the network utility. As a result of the nodes' iterative actions, the network utility tends to be maximized, while the total power consumption is converged to the minimum. To ensure that the transmission graph G^* reaches a steady state, we consider the notion of *local Nash network*, in which no node can improve

Algorithm 5: A coalitional graph game based approach for D2D data dissemination.

Input: $G(V, E)$, $P^*_{\max}$, $\gamma = F/\tau$, $B_i, \forall i \in V$, $|h_{ij}|^2$, $d_{ij}, \forall e_{ij} \in E$
Output: $G^*(V, E^*)$

1 **begin** Calculate power consumption of possible transmission links
2 **foreach** $e_{i,j} \in E$ **do**
3 Calculate $P_{t,i}$ with respect to receiver node j according to Eq. (4.2) such that $R_{ij} \geq \gamma$
4 **begin** Form transmission graph iteratively
5 $t \leftarrow 0$ *// Initialize iteration counter*
6 Initialize $G^*_t(V, E^*_t)$, where $E^*_t \leftarrow \varnothing$, and $U(G^*_t) = 0$
7 **foreach** $i \in V$ **do** *// Initialize states of nodes in V*
8 **if** $i = b$ **then**
9 Set $a_i = b_i = c_i = b$
10 **else**
11 Set $a_i = b_i = i, c_i = x$
12 **while** G^*_t *is not a local Nash network* **do**
13 Randomly select node $i \in V$
14 Request necessary information from BS for node i and calculate its set of feasible strategies S^*_i
15 Choose node i's local best response $s^*_i = \langle a^*_i, b^*_i \rangle$
16 Construct new transmission graph to $G^*_{t+1}(V, E^*_{t+1})$ according to s^*_i, where $E^*_{t+1} = (E^*_t \setminus \{e_{a_i i}, e_{i b_i}\}) \cup \{e_{a^*_i i}, e_{i b^*_i}\}$
  // Update c^*_i according to best response $\langle a^*_i, b^*_i \rangle$
17 **if** $a^*_i \neq i$ **then**
18 $c^*_i \leftarrow a^*_i$
19 **else**
20 $c^*_i \leftarrow c_i$
21 $(a_i, b_i, c_i) \leftarrow (a^*_i, b^*_i, c^*_i)$ *// Update node i's state*
22 $t \leftarrow t + 1$
23 Reconstruct final transmission graph $G^*(V, E^*)$ according to c_i in the state of node i, $\forall i \in V$
24 Return $G^*(V, E^*)$

the utility $U(G^*)$ by a unilateral change in its feasible strategy [54], *i.e.*, the graph finally converges to a local Nash network.

Alg. 5 gives the details of the proposed coalitional graph game. As seen, in Lines 1-3, we first need to calculate the required transmit power for all possi-

ble transmission links in graph $G(V, E)$ to meet the rate requirement. Then, in the main block (Lines 4-23), we iteratively build the transmission graph $G_t^*(V, E_t^*)$ by randomly selecting a node in each round t and applying its best response. Once $G_t^*(V, E_t^*)$ converges to a local Nash network, the iterations terminate and the final transmission graph $G^*(V, E^*)$ is reconstructed according to the node state information $c_i, \forall i \in V$.

4.2.3 A Walk-Through Example

To illustrate how the proposed coalitional graph game in Alg. 5 works, we introduce a walk-through example in this section. Fig. 4.4 gives a simple directed graph with 3 device nodes and the BS. The power budgets of nodes 1, 2, and 3, are 0.6, 1.0, and 0.8, respectively. As for the utility function, the parameter ϵ is set to 0.001. Here, for ease of exposition, we assume that each node accepts another node's request for a new link is accompanied by offering the established new link to other nodes. That is, after a node receives data from a newly established link, it will immediately request to transmit data to other nodes.

Fig. 4.5 shows the iterations of two running cases of Alg. 5 for the example in Fig. 4.4. Case 1 runs as follows.

1. Iteration 1: The BS is selected and plays its local best response, which is requesting to transmit data to other nodes.

2. Iteration 2: Node 1 is selected and accepts the BS's request for estab-

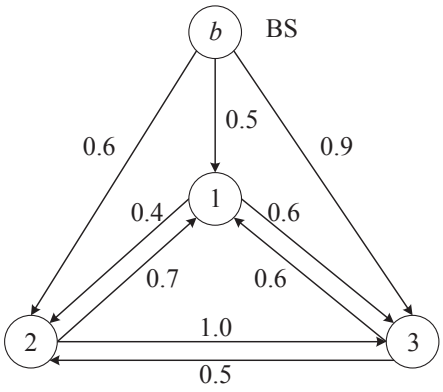
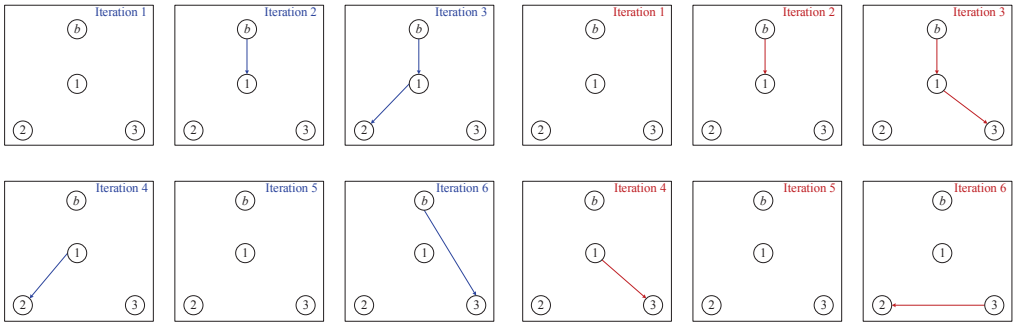


Fig. 4.4: An example graph for $G(V, E, w)$, where the power budgets of nodes 1, 2, and 3, are 0.6, 1.0, and 0.8, respectively.



(a) Case 1. (b) Case 2.

Fig. 4.5: Two running cases of Alg. 5 for the example graph in Fig. 4.4.

lishing the link $e_{b,1}$, as this strategy is the best maximizing the utility. Then, node 1's state is updated to $(b, 1, b)$.

3. Iteration 3: Node 2 is chosen. Since $P_{1,2} < P_{b,2}$, the local best response of node 2 is to accept the request of node 1 for the link $e_{1,2}$ and its state is updated to $(1, 2, 1)$.

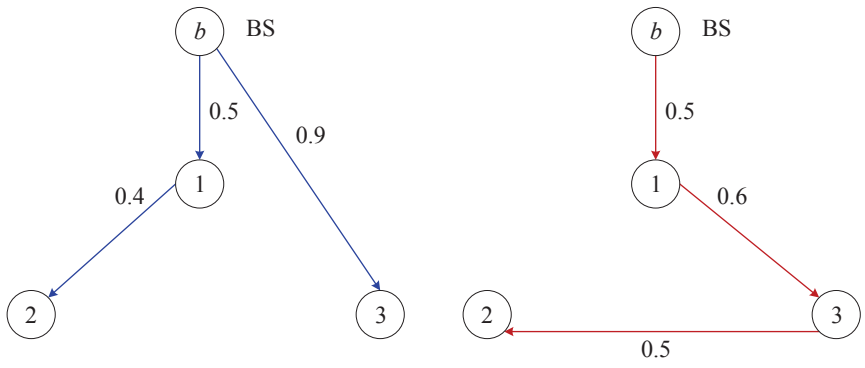
4. Iteration 4: The BS is selected again and breaks the link $e_{b,1}$ to explore more feasible receivers. Thus, the state of the BS is updated to (b, b, b) and the state of node 1 is updated to $(1, 2, b)$. Note that node 1's state indicates that there is no incoming link to node 1, while the previous upstream node that claims to send node 1 data is the BS.

5. Iteration 5: Node 1 is selected again. Similarly, the link $e_{1,2}$ is broken. The state of node 1 is updated to $(1, 1, b)$ and the state of node 2 is updated to $(2, 2, 1)$.

6. Iteration 6: Node 3 is selected. Although $P_{1,3} < P_{b,3} < P_{2,3}$, if node 3 chooses to receive data from node 1, the power consumption of node 1 will become $(0.4 + 0.6) = 1.0$. Note that node 1 has agreed to transmit to node 2 in iteration 4, which will consume power 0.4. Hence, this option will exceed the power budget of node 3, which is 0.6. Thus, node 3 chooses to receive data from the BS instead. The state of node 3 is then updated to $(b, 3, b)$. At this time, as no node improves the utility of the graph by a unilateral change in its feasible strategy, the graph converges to a local Nash network, and Alg. 5 terminates. Fig. 4.6(a) gives the reconstructed transmission graph. The utility of the formed graph is 1.203 and the corresponding total power consumption is 1.8.

Case 2 is shown in Fig. 4.5(b), in which the first two iterations are the same as those in case 1. In iteration 3, node 3 is selected alternatively. As $P_{1,3} < P_{BS,3}$, the local best response of node 3 is to accept the request of node

1 for the link $e_{1,3}$ and the state of node 3 is updated to $(1, 3, 1)$. Similarly, in iteration 4 and 5, the BS and node 1 are selected respectively and the links $e_{b,1}$ and $e_{1,3}$ are broken. In iteration 6, node 2 is selected. Although $P_{1,2} < P_{3,2} < P_{BS,2}$, if node 2 receives data from node 1, the power budget constraint of node 1 is not satisfied. Thus, node 2 chooses to receive data from node 3 instead. At this time, the formed graph converges to the local Nash network. Fig. 4.6(b) gives the generated transmission graph, which is actually the optimal solution to problem (4.3). The utility of the formed graph is 1.403 and the corresponding total power consumption is 1.6. As seen in the two cases, due to the random selection of nodes in each iteration and the condition of local Nash network, each running case of Alg. 5 may converge to a different transmission graph.



(a) Result of case 1.

(b) Result of case 2.

Fig. 4.6: Reconstructed transmission graphs of the two running cases in Fig. 4.5, which give total power consumption of 1.8 and 1.6, respectively.

4.3 Simulation Results

To evaluate the performance of our proposed approach, we conduct computer simulations with a 200m×200m square region, in which the BS is located at the center point, and the cellular users and D2D users are uniformly distributed. The number of cellular users is fixed at 150, while the number of D2D users varies in the simulations. Each D2D user is assigned an arbitrary cellular uplink channel for its D2D communications. The D2D transmission range is set to 100m. The transmit power of cellular users is set to 24dBm and the carrier bandwidth is set to 1MHz. The data rate demand for the message is set to 1MB/s. The path-loss exponent and noise variance are set to $\alpha = 1$ and $\sigma^2 = 5 \times 10^{-7}$ mW, respectively. We use the caveman model with different rewiring probabilities to generate the social relationships among the D2D users. In order to specify a user's power budget constraint, we define a factor called *budget ratio*, which is the ratio of the power that a user would spend in transmitting data to its friends within the D2D communication range over its potential total power.

4.3.1 Convergence Performance

First, we show the convergence performance of our proposed coalitional graph game for the network with 15 (n) D2D users. The social relationships are modeled by the caveman model. Here, we set the number of caves to 3, the size of each cave to 5, and the rewiring probability p to 0.1. The budget

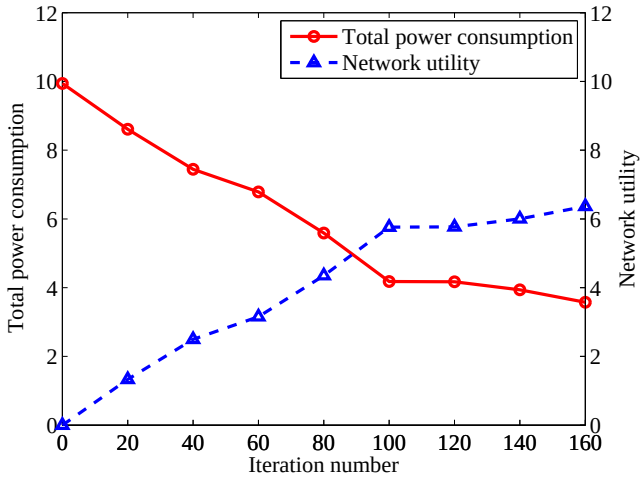


Fig. 4.7: Convergence performance of the proposed coalitional graph game with $n = 15$.

ratio of each user is set within the range of $(0.5, 1]$. Fig. 4.7 shows the network utility and total power consumption of the proposed approach versus the iterations respectively. As observed, the network utility first increases rapidly and then converges gradually. Meanwhile, we can see that the corresponding total power consumption decreases gradually and finally reaches a low value. This is because our definition of utility is inversely proportional to the total power consumption, such that as the utility increases, the total power consumption decreases correspondingly.

4.3.2 Comparison of Different Solutions

Next, we compare our proposed approach with three reference schemes. The first reference scheme is introduced at the beginning of Section 4.2 which can find an optimal solution to problem (4.3). The second scheme is a distributed

heuristic approach, in which one of the nodes that have received data is randomly selected in each iteration and the node transmits data to the feasible receiver which consumes the lowest power. This approach iterates until all nodes in the network have received the data. Third, we consider a different coalitional graph game that extends the basic idea of [32] to problem (4.3). In [32], the BS is regarded as the initial source, and a transmission graph $\hat{G}(V, \hat{E})$ coordinating the data dissemination is built from the initial directed graph $G(V, E)$ via a coalitional graph game. Here, the utility function is defined similarly as $U(\hat{G}) = \sum_{e_{ij} \in \hat{E}} (m_i - m_j)(w_{\max} - w(e_{ij}))$, where m_i (resp. m_j) is binary indicating whether i (resp. j) has possessed the data, and $w_{\max}$ is the maximum weight of edges in E.

First, we run simulations with relatively small-scale networks and different social connection structures. Here, all the parameter settings are the same as those specified in the previous simulation with 15 D2D users, except that the rewiring probability p ranges from 0 to 0.5 to generate social networks of different characteristics. Fig. 4.8 shows the total power consumption with different social structures. As seen, the total power consumption of our approach is fairly close to that of the optimal solution with different social relationships. The total power consumptions of the two reference schemes are both higher than that of our approach, among which the scheme based on a different coalitional graph game has the highest power consumption. In this scheme, after a node receives data from another node, it cannot accept any link request from a more efficient source, since accepting such a

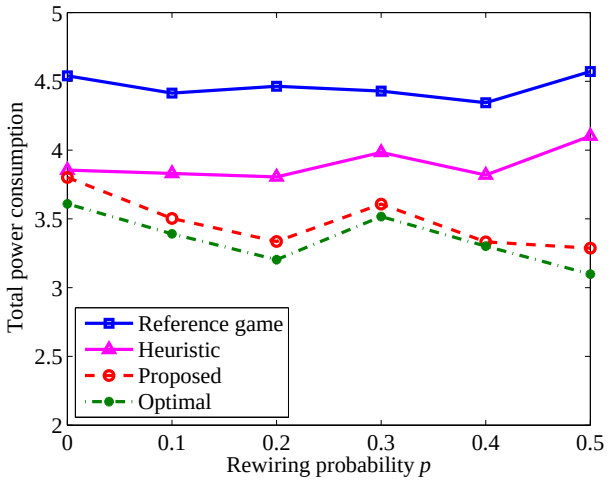


Fig. 4.8: Comparison of data dissemination schemes with different social structures and $n = 15$.

request means the term $(m_i - m_j)$ in the utility function will be zero and thus cannot increase the utility. This design is to aggressively avoid forming a cycle without a source, even though not every such request will lead to an undesired cycle. By contrast, our proposed coalitional graph game relaxes this limitation and allows nodes to accept the requests from other nodes for establishing more efficient links as long as no cycle without a source will result from such actions.

4.3.3 Scalability to Large Networks

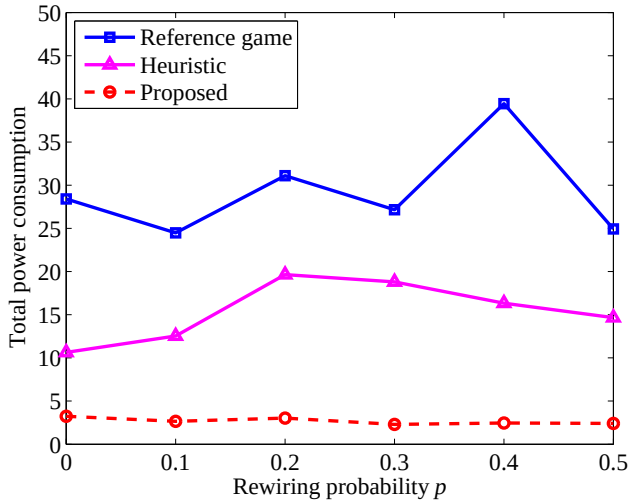
In the following, we run simulations with larger-scale networks. As mentioned in Section 4.2, it is very difficult to obtain the optimal solution to problem (4.3). Especially, with a larger network scale, the search space of the graph becomes much broader. As a consequence, it becomes extremely difficult to

obtain the optimal solution. Therefore, in the following simulations, we only compare our solution with the heuristic approach and the other coalitional graph game based approach. Here, we consider networks with 50 and 100 D2D users, while the number of caves is set to 5 and 10, respectively, given that the cave size is fixed at 10. The budget ratio of each user is set within the range of $(0.5, 1]$ and the rewiring probability p varies from 0 to 0.5.

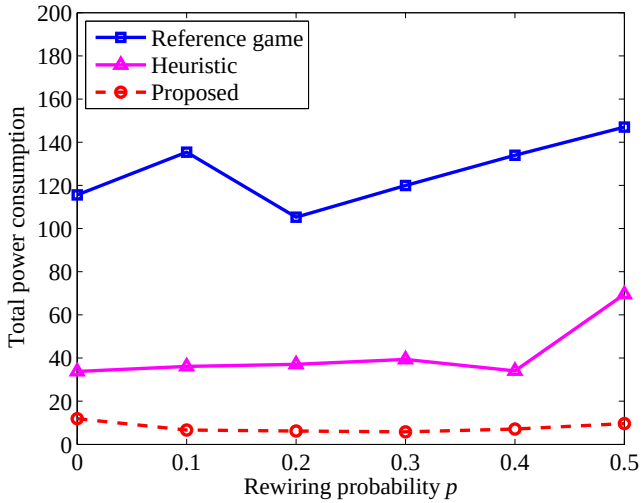
Fig. 4.9 shows the total power consumption of three data dissemination schemes with different network scales. As seen in both Fig. 4.9(a) and Fig. 4.9(b), the total power consumption of our solution is always lower than that of the two reference schemes. It is worth noticing that, when the network scale increases, the gap between our solution and the reference schemes becomes more significant. This demonstrates that our approach is more adaptive to networks of different sizes, and especially more scalable to large networks. Meanwhile, it can be observed in both scenarios that, with the increase of the rewiring probability, the total power consumption of our solution fluctuates within a narrower range while the two reference schemes fluctuate more dramatically. This indicates that our approach is also more adaptive to different social connection structures and power budget constraints.

4.3.4 Impact of Power Budget Constraint

Last, we test the impact of users' power budget constraints on the performance of data dissemination. Here, we use similar settings as the simulation



(a) $n = 50$.



(b) $n = 100$.

Fig. 4.9: Comparison of data dissemination schemes with large D2D networks.

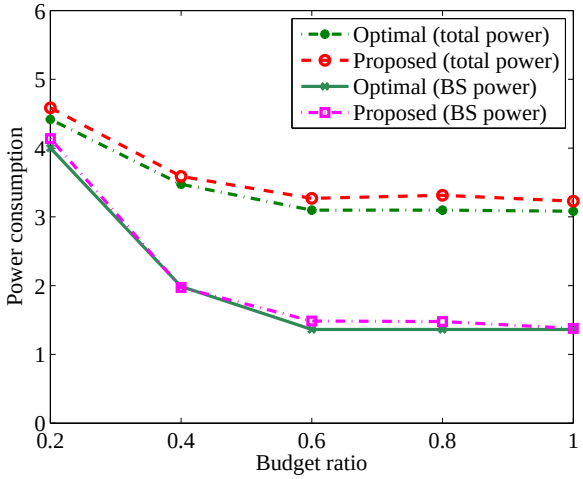


Fig. 4.10: Impact of users' power budget constraint on data dissemination performance with $n = 15$.

with 15 D2D users in Section 4.3.1. The rewiring probability p is set to 0.5, while the cave size remains to be 5 and there are 3 caves. In order to reflect the impact of users' power budget constraint, we assume the same budget ratio for each user and vary the ratio from 0.2 to 1.

Fig. 4.10 shows the total power consumption and the BS's power consumption versus the budget ratio. As seen, the power consumption of our approach is fairly close to that of the optimal solution in all cases with various power budgets. Besides, as expected, the power consumption decreases with a larger budget ratio. In particular, when the budget ratio increases from 0.2 to 0.4, the power consumption of the BS is reduced substantially. This is because the larger power budget allows users to contribute more energy in transmitting data to their friends within the D2D communication range. Thereby, more efficient D2D links can be utilized to offload data transmission from the BS.

Furthermore, when the budget ratio exceeds certain threshold (say, 0.6), the power consumption becomes more stable. This is because after certain point most efficient D2D links have already been selected. Even when the users would like to contribute more energy, the selected D2D links will rarely change.

4.4 Summary

In this chapter, we investigate how to explore social connections and D2D communications for energy-efficient data dissemination to minimize the total power consumption of data dissemination. To enable data dissemination in practice, we take into account both social incentive constraint and power budget constraint of D2D users. As it is computationally difficult to obtain an optimal solution to the formulated data dissemination problem, we propose a coalitional graph game to approach the optimal solution. Our approach iteratively derives a transmission graph for data dissemination to select seeds and coordinate subsequent transmission. The simulation results show that the power consumption of our proposed approach is fairly close to that of the optimal solution in a small-scale D2D network. Moreover, our approach outperforms two other reference schemes in various cases with different network sizes and social structures. We also demonstrate the convergence performance of our approach and the effect of users' power budgets on the performance of data dissemination.

Chapter 5

Social Community Based Data Dissemination

In the previous two chapters, users' social connections with their direct friends in the unweighted social network are explored for data dissemination. As people generally prefer to interact with their direct social connection due to the concerns of trust and security, we assume that D2D data dissemination only occurs between two directly socially connected users. In fact, in the real life, some people may also be willing to interact with others who are in the same social communities and indirectly connected with them, as long as the social connection is strong enough. In this chapter, we further take into account users' weighted social relationships with the members in their social communities. Correspondingly, users' social connection strength and multiple-hop connection with others in the social communities need to

be properly utilized for data dissemination.

In this chapter, we propose a preference-aware two-phase mechanism for data dissemination, which aims at maximizing target users' preferences for messages. In Phase I, the BS first delivers the content to certain selective users called seeds or initial sources, which have the maximum potential coverage abilities. The source selection problem is modeled as a weighted maximum coverage problem and solved by an approximate algorithm. In phase II, the selected sources further forward data to the remaining target users. We design a monetary mechanism and a moneyless mechanism to incentivize sources to perform data forwarding. Our evaluations via synthetic and real tracing dataset show that our proposed data dissemination scheme can achieve high total utility and average completion ratio. Table 5.1 lists the symbols used in this chapter.

5.1 System Model

5.1.1 Data Dissemination Model

We consider a data dissemination scenario depicted in Fig. 5.1. A set of devices, N, are requesting messages from set M. The devices are uniformly distributed in a cellular region, which is served by the BS. Each device $i \in N$ requests one message $k \in M$, following an independent distribution. Assume that each user holding device $i \in N$ has a preference toward the requested message k, which is quantified by a normalized valuation (i.e., utility), g_{ik},

Table 5.1: Symbols for Chapter 5.

Symbol	Definition
N	Set of devices
M	Set of messages
g_{ik}	Preference of the user holding device i toward the requested message k
S	Set of initial sources
$\hat{S}$	Set of initial sources plus a dummy source
R	Set of request devices
$\hat{R}$	Set of request devices plus a dummy request device
l_i	Maximum number of messages that source i can transmit to request devices
d_{max}	Collaboration distance
x_i	Signal transmitted from device i
y_j	Received signal at device j
$P_{t,i}$	Transmit power of device i
h_{ij}	Channel response of link from device i to device j
n_j	Additive white Gaussian noise at device j
r_{ij}	Maximum data rate achievable for D2D link from i to j
B_{ij}	Bandwidth of resource blocks allocated to D2D link from i to j
d_{ij}	Distance between device i and device j
α	Path loss exponent
G	Weighted social network graph
E	Set of edges corresponding social connections between users
w_{ij}	Strength of social connection between user i and user j
$w(P_{ij})$	Weight of path P_{ij} that connects user i and user j without repeated vertices in graph G
$d(P_{ij})$	Social distance between user i and user j via path P_{ij}
l_w	Threshold of social connection strength
C_i	Subset of devices in N that device i can forward data to
$\mathcal{P}_{ij}$	Set of all possible paths between i and j in social network graph G
s	Number of initial sources to be selected
v_{ij}	Valuation of request device j toward source i
r_{min}	Minimum transmission rate between request device and source
w_{max}	Largest social tie strength over any path in social network G
x_{ij}	Indicating whether source i is assigned to send message to request device j
$\hat{v}_{ij}$	Bid of request device j toward source i
$p_j^{(\mathrm{R})}$	Payment made by request device j to the BS
$p_i^{(\mathrm{BS})}$	Payment made by the BS to source i

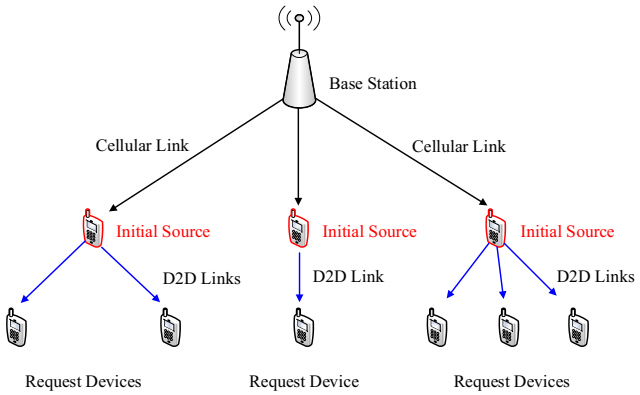


Fig. 5.1: Data dissemination scenario.

where $0 < g_{ik} \leq 1$. The BS first chooses a subset of the devices as initial sources, denoted by S, $S \subset N$, and directly transmits the messages to them. After that, the initial sources forward the messages to the unfulfilled remaining devices, called request devices, via D2D communications underlaying the cellular network. Here, the set of request devices is denoted by R, where $R = N \setminus S$. Each source $i \in S$ can transmit at most l_i ($l_i \geq 1$) messages to the request devices in the network. Our system goal is to maximize the total utility of the devices that successfully receive the requested messages.

The difference of the data dissemination scenario considered in this chapter and that adopted in Chapter 3 and Chapter 4 is the scope of D2D communications in the network. D2D communication scope among users can be multi-hop in previous two chapters but is one-hop in this chapter. This is because, in this chapter, we aim to explore the direct interactions between sources and request devices. An example real application scenario of the data dissemination model in this chapter is data dissemination in a shopping

mall, where a customer generally stays in a store for some time and then goes to another store. Since customers' positions are not fixed, multiple-hop D2D communication chains are not guaranteed to form. Thus, in such a circumstance, one-hop D2D communication is more robust and reliable.

5.1.2 D2D Channel Model

We consider a D2D channel model, which is slightly different from that adopted in the previous two chapters. Here, each D2D communication link is allocated an orthogonal uplink channel of a distinct cellular user. Hence, there is no interference among D2D links. In addition, by employing advanced D2D resource allocation schemes [55], the interference from cellular users can be controlled to be substantially low. For instance, if a D2D link is allocated an unused cellular channel, it is not subject to interference from a cellular user. The D2D link can also share the channel of a distant cellular user that causes negligible interference. Two user devices can directly communicate with each other via D2D communications under the control of the BS, if their distance is within a collaboration distance $d_{\max}$ [56]. Then, for a D2D link from transmitting device i to receiving device j, the received signal at device j can be written as

$$y_j = \sqrt{P_{t,i}} h_{ij} x_i + n_j \tag{5.1}$$

where x_i is the signal from device i transmitted with power $P_{t,i}$, and h_{ij} is the channel response of the link from i to j, and n_j is the additive white Gaussian noise at device j. Therefore, the maximum data rate achievable for the D2D link from i to j is given by

$$r_{ij} = B_{ij} \cdot \log_2 \left(1 + \frac{P_{t,i} \cdot |h_{ij}|^2}{|n_j|^2} \right) \tag{5.2}$$

where B_{ij} is the bandwidth of the resource blocks allocated to the D2D link from i to j. Consider a Rayleigh fading channel model with log-distance path loss. The received signal power at j, *i.e.*, $P_{t,i} \cdot |h_{ij}|^2$, is exponentially distributed with mean $P_{t,i} \cdot d_{ij}^{-\alpha}$, where d_{ij} is the distance between i and j, and α is the path loss exponent.

5.1.3 Social Network Model

In Chapter 3 and Chapter 4, as in many previous studies [32,57], it is assumed that D2D-based data forwarding only occurs between two users with direct social connection to accommodate the incentive constraint. This is reasonable since altruistic behaviours are observed among people with social trust (*e.g.*, family members, friends, and colleagues), and people are motivated to adopt a generous action that benefits their direct social contacts at their own costs. Hence, users' social relationships can be modeled by an unweighted graph, which actually defines either value 0 for a non-existent link or value 1 for a present link between any two users, corresponding to the

weakest or strongest connection, respectively.

Nonetheless, in the real life, there can also exist some people who would like to interact with those indirect social contacts in their social communities if their social relationships are strong enough. Thereby, in this chapter, we further extend the social network model of previous two chapters in two aspects. First, we consider a weighted graph, $G(N, E, w)$, to model the social relationships among mobile users, where N is the set of devices held by these users, E is the set of edges corresponding the social connections between these users, and each edge is labelled by a weight. For example, weight w_{ij}, $0 < w_{ij} \leq 1$, defines the strength of the social connection between user i and user j. As such, the social tie strength between any two users falls within $[0, 1]$, ranging from no social contact whatsoever to the strongest direct social relationship. This notion is more general than the 0-1 model for social connections.

Second, we extend the data dissemination scope of a mobile user, including not only those users with direct links with the current user in the social network graph, but also certain users in its social community. Here, one connected component of graph G is called a social community, in which any two users are connected in some manner via direct or indirect links. To quantify the strength of an indirect social connection, we define the weight of path P_{ij} that connects i and j without repeated vertices as

$$w(P_{ij}) = \prod_{e=(a,b)\in E,\ e\in P_{ij}} w_{ab}. \tag{5.3}$$

Here, a larger value of the weight reflects a higher level of closeness. Then, we limit that user i performs data forwarding via a D2D link to user j in its social community only if there exists a path P_{ij} such that $w(P_{ij})$ is not less than a threshold, l_w. To facilitate computation of the weights, we also define the social distance between i and j via path P_{ij} as follows:

$$d(P_{ij}) = \sum_{e=(a,b)\in E,\ e\in P_{ij}} \log \frac{1}{w_{ab}}. \tag{5.4}$$

As seen, a shorter social distance implies a stronger social connection. Since multiple paths can exist from i to j in the social network graph, we use the Floyd-Warshall algorithm to find a shortest-distance path and then compute the corresponding weight.

5.2 Social-Aware Data Dissemination with Incentive Constraints

In the data dissemination scenario shown in Fig. 5.1, there are two critical phases, *i.e.*, initial source selection and data forwarding between selected sources and request devices. The sources' social trust with the socially connected users in the social community justifies their willingness to transmit messages for others. The first important problem is how to effectively utilize users' social relationships in the social community to select the initial sources. In the subsequent data forwarding through D2D communications,

the sources should be appropriately paired with request devices while the incentive constraints are accommodated. Here, we consider both monetary and moneyless incentives for data forwarding between selected sources and request devices. The proposed monetary mechanism is based on a forward auction, while the moneyless mechanism determines a many-to-one stable matching.

5.2.1 Initial Source Selection

In this section, we introduce the proposed initial source selection algorithm. Since our system goal is to maximize the total utility of the receiving devices, a natural idea is to select a certain number of sources such that the union set of the devices that can be potentially covered by these sources achieves the maximum total utility. Here, the number of initial sources, denoted by s, can be adjusted according to the energy and bandwidth limits of the BS. If device i in set N is selected as an initial source and receives its request message directly from the BS, then this device can forward the message to a subset of devices in N, denoted by C_i, where each device $j \in C_i$ should: i) request the same message, ii) fall within the collaboration range $d_{\max}$, and iii) belong to the same social community as user i and has a social weight $\max_{P \in \mathcal{P}_{ij}} w(P) \geq l_w$, where $\mathcal{P}_{ij}$ is the set of all possible paths over any possible path between i and j in the social network graph G. The maximum total utility achievable by source i is the summation of the utilities of device i and its covered devices in C_i toward their requested messages.

Correspondingly, we formulate the above source selection problem as a weighted maximum coverage problem, where the universe of elements is the set of devices N, the set of subsets for selection is $\cup_{i \in N} C_i$, and each subset corresponding to a potential source is associated with an achievable utility as the weight. As the maximum coverage problem is NP-hard, we use the following iterative algorithm with an approximation ratio of $1 - 1/e$. Initially, all devices in N are marked as uncovered. Then, in each iteration, the algorithm selects a new source among all uncovered devices, which achieves the highest total utility with respect to itself and the uncovered devices in the subset that this device can potentially serve. Then, the selected source and these uncovered devices in the subset are marked as covered, and will not be considered in the future iterations. The subset of devices that are newly covered by a selected source i is denoted by $\tilde{C}_i$, where $\tilde{C}_i \subseteq C_i$. The algorithm keeps iterating until s sources are selected or all devices in N are marked as covered. The set of selected initial sources is denoted by S, where $|S| \leq s$. Alg. 6 shows the details of the source selection algorithm.

5.2.2 A Monetary Incentive Mechanism Based on Forward Auction

According to the source selection algorithm in Section 5.2.1, the BS can recruit a group of source devices to forward their received messages from the BS to remaining request devices. To incentivize the selected sources

Algorithm 6: The initial source selection algorithm.

Input: Device set N, social network graph G, locations, requested messages, and transmit limits of all devices
Output: Source set S

1 $S \leftarrow \varnothing$
2 **begin** Obtain coverage subset for each device in N
3 **for** *each device* i *in* N **do**
4 $C_i \leftarrow \varnothing$
5 **for** *any other device* j *in* N, $j \neq i$ **do**
6 **if** $m_i = m_j$, $d_{ij} \leq d_{\max}$, *and* i *and* j *belong to same social community with* $w(P_{ij}) \geq l_w$ **then**
7 $C_i \leftarrow C_i \cup j$
8 $u_i(C_i) \leftarrow g_{i,m_i} + \sum_{j \in C_i} g_{j,m_j}$ *// Max utility achievable by coverage of device* i
9 **begin** Select initial sources from all devices in N
10 $\tilde{N} \leftarrow N$ *// $\tilde{N}$ is the set of remaining candidates for sources*
11 $\tilde{C}_i \leftarrow C_i$ *// $\tilde{C}_i$ is the set of uncovered devices in C_i*
12 **while** $|S| < s$ *and* $\tilde{N} \neq \varnothing$ **do**
13 Rank devices in descending order of $u_i(\tilde{C}_i)$, $\forall i \in N$
14 Select top device $j \in \tilde{N}$, and update $S \leftarrow S \cup j$ *// Add new source* j
15 $\tilde{N} \leftarrow \tilde{N} \setminus j$
16 **for** *each device* $i \in \tilde{N}$ *and* $\tilde{C}_i \cap (C_j \setminus \tilde{C}_j) \neq \varnothing$ **do**
17 $\tilde{C}_i \leftarrow (\tilde{C}_i \setminus (C_j \setminus \tilde{C}_j))$ *// Remove devices covered by source* j
18 Update $u_i(\tilde{C}_i)$ as in line (8)
19 Return source set S

to forward data for others, the sources can be provided monetary rewards. An auction provides an effective means to efficiently distribute the resources of the source devices at competitive prices. An auction can be a forward auction, a reverse auction, or a double auction. In a forward auction, buyers submit bids according to their valuations toward the auction items, while an auctioneer chooses the winning buyers to maximize the total valuation of winners and determines the clearing prices. In contrast, in a reverse auction

(also known as procurement auction), sellers compete to obtain contracts by submitting asks based on their resource costs. The auctioneer often chooses the winning sellers to minimize the total resource cost and pays the winners. A double auction actually creates an exchange environment consisting of both buyers and sellers. The auction outcome depends on buyers' bids and sellers' asks to accommodate their valuations and costs. Due to the more complex conflicting interests of buyers and sellers in a double auction, there does not exist any mechanism that is efficient, truthful, individually rational, and budget-balanced at the same time [58].

In this work, we take advantage of the intermediate role of the BS to deal with the sources and request devices separately. First, the BS sets up a forward auction that allocates the resources of the sources to the request devices and determines the payments of the request devices that are the ultimate data consumers. Each request device submits a bid for each source that is within its receiving range and contains its desired message. In a truthful auction, the submitted bid should be equal to the actual valuation of the request device toward the source. As given in the following definition, we consider three main attributes to determine the valuation of a request device toward a source, including the preference of the request device for the requested message, the available transmission rate of the source, and the strength of the social tie between the request device and the source.

Definition 2. *The valuation of request device $j \in R$ that asks for message*

$k \in M$ toward source $i \in S$ is defined as a weighted sum [52], given by

$$v_{ij} = \begin{cases} \omega_{j_1} \cdot g_{jk} + \omega_{j_2} \cdot \beta \tanh\left(\frac{\gamma \cdot r_{ij}}{r_{\min}}\right) + \omega_{j_3} \cdot \frac{\max_{P \in \mathcal{P}_{ij}} w(P)}{w_{\max}}, & \textit{if } i \textit{ caches message } k \\ 0, & \textit{otherwise} \end{cases} \tag{5.5}$$

where

$$\omega_{j_1} + \omega_{j_2} + \omega_{j_3} = 1.$$

Here, ω_{j_1}, ω_{j_2}, and ω_{j_3} are the weights of device j corresponding to three attributes in the valuation. In addition, g_{jk}, $0 < g_{jk} \leq 1$, is the preference of request device j for the requested message k that source i caches, $\tanh(\cdot)$ is the hyperbolic tangent function, β and γ are constants to scale the input and output values of $\tanh(\cdot)$, r_{ij} is the available transmission rate between i and j, $r_{\min}$ is the requirement for the minimum transmission rate between a request device and a source, $\max_{P \in \mathcal{P}_{ij}} w(P)$ is the largest social weight between i and j, and $w_{\max}$ is the largest social tie strength over any path in the social network G. Note that $\beta \tanh(\cdot)$ in the second term and the ratio in the third term normalize the corresponding attributes to the range of $[0, 1]$. The reason that we choose the hyperbolic tangent function is that its increase with the input parameter r_{ij} becomes slower when r_{ij} is larger, which well captures the diminishing marginal increase.

Based on the bids of request devices, the BS chooses at most one source to serve each request device, such that the total valuation of the fulfilled request devices is maximized. This choice rule can be modeled mathematically as

follows:

$$\text{max.} \quad \sum_{i \in S} \sum_{j \in R} \hat{v}_{ij} \cdot x_{ij} \tag{5.6a}$$

$$\text{s.t.} \quad \sum_{i \in S} x_{ij} \leq 1, \quad \forall j \in R \tag{5.6b}$$

$$\sum_{j \in R} x_{ij} \leq l_i, \quad \forall i \in S \tag{5.6c}$$

$$x_{ij} \in \{0, 1\}, \quad \forall i \in S, j \in R. \tag{5.6d}$$

In (5.6a), binary variable x_{ij} indicates whether source i is assigned to send the message to request device j, and $\hat{v}_{ij}$ is the bid of request device j toward source i. Here, we do not use real valuation v_{ij} just to highlight that the truthfulness assumption that $\hat{v}_{ij} = v_{ij}$ remains to be validated. Constraint (5.6b) requires that each request device be served by one source with its desired message. Constraint (5.6c) defines the limit of each source in the maximum number of transmission messages. Constraint (5.6d) is the integer constraint for the decision variable x_{ij}.

To solve problem (5.6), we translate it to an instance of the transportation problem [59], which is solvable in polynomial time. The transportation problem is often defined in the context of distributing a set of commodities from a group of supply centres, termed sources, to a group of receiving centres, termed destinations, with the goal of minimizing the total distribution cost. Every source has a fixed supply of units to be distributed to the destinations, while every destination has a fixed demand for the units received from the

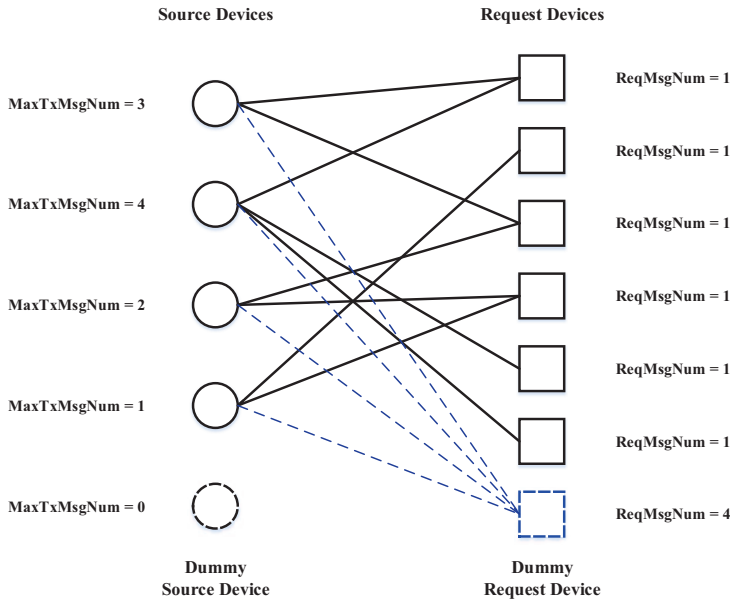


Fig. 5.2: Transportation problem modeling.

sources. Fig. 5.2 illustrates the formulation of problem (5.6) as a transportation problem. Here, the request devices are considered as destinations, and the number of requested messages of a request device is considered as the demand of a destination. The selected source devices are modeled as sources, and the maximum number of transmission messages by a source is modeled as its supply. Last, we consider $(-\hat{v}_{ij})$ as the distribution cost from source i to destination j.

However, such a transportation problem can be unbalanced, *i.e.*, the total demand of request devices may not be equal to the total supply of initial sources. Hence, if the total demand is greater than the total supply, we adapt the set of sources S to $\tilde{S}$ by adding a dummy source, which provides

a supply of the difference and has a zero cost toward every request device. On the other hand, if the total demand is less than the total supply, we add a dummy request device and extend R to $\tilde{R}$. Similarly, the dummy request device is subject to a zero cost to every source and has a demand of the difference. Based on this modeling, we can reformulate problem (5.6) to a balanced transportation problem as follows:

$$\text{min.} \quad \sum_{i \in \tilde{S}} \sum_{j \in \tilde{R}} (-\hat{v}_{ij}) \cdot x_{ij} \tag{5.7a}$$

$$\text{s.t.} \quad \sum_{i \in \tilde{S}} x_{ij} = 1, \quad \forall j \in \tilde{R} \tag{5.7b}$$

$$\sum_{j \in \tilde{R}} x_{ij} = l_i, \quad \forall i \in \tilde{S} \tag{5.7c}$$

$$x_{ij} \in \{0, 1\}, \quad \forall i \in \tilde{S}, j \in \tilde{R}. \tag{5.7d}$$

As seen in (5.7), the two inequality constraints in (5.6) are replaced by equality constraints. Then, the transportation problem can be solved very fast, by first constructing an initial basic feasible solution using the north-west corner method or the least-cost method, and then iteratively improving the current feasible solution until convergence to the optimum.

The optimal solution to problem (5.7) maximizes the total declared valuation of all bidding request devices. This is actually consistent with the choice rule of the VCG mechanism. To further validate the truthfulness assumption, we follow the pricing rule of the VCG mechanism to determine the price paid

by each winning request device. Specifically, the payment made by request device j to the BS is given by

$$p_j^{(\mathrm{R})} = \sum_{i \in S} \sum_{j' \in R, j' \neq j} \hat{v}_{ij'} \cdot x_{ij'}^{(\mathrm{OPT})}(\hat{v}_{-j}) - \sum_{i \in S} \sum_{j' \in R, j' \neq j} \hat{v}_{ij'} \cdot x_{ij'}^{(\mathrm{OPT})}(\hat{v}). \quad (5.8)$$

Here, $x_{ij'}^{(\mathrm{OPT})}(\hat{v}_{-j})$, $\forall i \in S, j' \in R$, denotes the optimal solution to (5.7) if request device j does not exist. Thus, the first summation term is the maximum valuation achieved by this optimal solution. In the second summation term, $x_{ij'}^{(\mathrm{OPT})}(\hat{v})$, $\forall i \in S, j' \in R$, denotes the optimal solution to (5.7) when request device j is considered, while the summation excludes the valuation achieved by request device j from the total valuation. In fact, the payment paid by request device j is the loss of the total valuation of the other request devices caused by the presence of j.

Based on the payments that the BS collects from the request devices, the BS pays the sources based on their contributions. According to the number of their forwarded messages and the corresponding message sizes, the BS pays source $i \in S$ as follows:

$$p_i^{(\mathrm{BS})} = \sum_{k=1}^{k_i} f(L_k) \quad (5.9)$$

where k_i, $1 \leq k_i \leq l_i$, is the number of messages that source i forwards, and L_k is the size of its kth forwarded message, and function $f(\cdot)$ is a monotonic non-decreasing function that determines a monetary payment proportionally to the message size. In the numerical experiments in Section 5.3, we use a

Algorithm 7: The data forwarding process with monetary incentives based on forward auction.

Input: Source set S, set of request devices R, social network graph G, transmit limits of sources $\{l_i, \forall i \in S\}$

Output: Pairing result $\{x_{ij}, \forall i \in S, j \in R\}$, pricing result $\{p_j^{(\mathrm{R})}, j \in R\}$ and $\{p_i^{(\mathrm{BS})}, i \in S\}$

begin Construct bids of request devices
  for *each device* $j \in R$, *each device* $i \in S$ **do**
    Compute $\hat{v}_{ij}$ according to definition in (5.5)
begin Construct forward auction to determine device pairing and pricing
  Obtain optimal solution, $\{x_{ij}^{(\mathrm{OPT})}(\hat{v}), \forall i \in S, j \in R\}$, to problem (5.6) based on transportation problem
  for *each request device* $j \in R$ **do**
    if $\sum_{i \in S} x_{ij}^{(\mathrm{OPT})}(\hat{v}) = 1$ **then** *// Request device j wins in auction*
      Obtain optimal solution, $\{x_{ij}^{(\mathrm{OPT})}(\hat{v}_{-j}), \forall i \in S, j \in R\}$, to problem (5.6) assuming device j didn't exist
      Determine payment by request device j, $p_j^{(\mathrm{R})}$, according to (5.8)
    else
      $p_j^{(\mathrm{R})} \leftarrow 0$
begin Determine rewards to source devices
  for *each source device* $i \in S$ **do**
    if $\sum_{j \in R} x_{ij}^{(\mathrm{OPT})}(\hat{v}) \geq 1$ **then** *// Source i wins in auction*
      Determine reward to source i, $p_i^{(\mathrm{BS})}$, according to (5.9)
    else
      $p_i^{(\mathrm{BS})} \leftarrow 0$
Return $\{x_{ij}^{(\mathrm{OPT})}(\hat{v}), \forall i \in S, j \in R\}$, $\{p_j^{(\mathrm{R})}, j \in R\}$ and $\{p_i^{(\mathrm{BS})}, i \in S\}$

linear function for $f(\cdot)$.

The entire procedure of the monetary incentive mechanism is summarized in Alg. 7. As seen, there are two main steps for the BS to determine the payments collected from the request devices and the rewards paid to the

sources devices. Truthfulness is a critical property of a monetary incentive mechanism, because the data dissemination ecosystem would become unstable and unpredictable if the sources could cheat to increase their payoff. We can show that the monetary incentive mechanism in Alg. 7 is truthful. First, the payments of the request devices are determined according to the pricing rule of the VCG mechanism, which is dominant-strategy truthful [60]. Second, the payment by the BS to a source depends on the attributes of the transmitted messages, which are measurable and verifiable. Therefore, the sources are expected to be truthful in declaring the information of their forwarded messages to claim their payments, since the BS can verify such information from the receiving devices served by the sources. Overall, the monetary incentive mechanism in Alg. 7 is truthful.

5.2.3 A Moneyless Incentive Mechanism Based on Stable Matching

In the previous section, we propose an auction-based mechanism to incentivize sources to forward data for request devices. Nonetheless, in some circumstances, the transfer of money may be a hassle due to the payment overhead or security concern. Hence, a moneyless incentive mechanism is more convenient in such situations. In this work, we also propose a matching-based moneyless mechanism. For the moneyless incentive mechanism, stability is an essential requirement so that the request devices and sources are willing

to accept a pairing result.

Considering the bipartite graph in Fig. 5.2, we can formulate a stable matching problem based on the preferences of the request devices and sources. For each request device $j \in R$, based on the valuation definition in (5.5), we obtain its strict preference order with respect to the sources in set S. That is, for request device j, $\forall i_1, i_2 \in S$, $i_1 \succ_j i_2$ if and only if $v_{i_1 j} > v_{i_2 j}$.

On the other hand, the valuation of a source toward a request device is defined as follows.

Definition 3. *The valuation of source $i \in S$ toward request device $j \in R$ that requests message $k \in M$ is given by*

$$u_{ij} = \begin{cases} f(L_k) - (1 - \lambda \cdot \max_{\forall P \in \mathcal{P}_{ij}} w(P)) \cdot \varphi\left(\frac{P_{t,i} \cdot L_k}{r_{ij}}\right), & \text{if } i \text{ caches message } k \\ 0, & \text{otherwise.} \end{cases} \tag{5.10}$$

Here, L_k is the size of message k that is requested by device j and forwarded by source i if source i caches it, and $f(L_k)$ is the payment received by i from the BS. As $P_{t,i}$ is the transmit power of source i and r_{ij} is the transmission rate from i to j, the term $(P_{t,i} \cdot L_k / r_{ij})$ actually gives the transmission energy consumption of source i. Function $\varphi(\cdot)$ is a monotonic non-decreasing function that maps the energy consumption to a monetary cost. Basically, the source's valuation is defined as the difference of the payment received from the BS and the cost. Moreover, we further incorporate a coefficient weighted by the social relationship between source i and request device j. This is to

characterize the user's subjective perception toward a cost depending on the strength of the social connection. Generally, people tend to be more altruistic to those with strong social ties and thus they are willing to devote more resources to help them. Hence, in (5.10), the cost output from function $\varphi(\cdot)$ is weighted by a coefficient, $(1-\lambda\cdot\max_{\forall P\in\mathcal{P}_{ij}} w(P))$, in which λ is a constant in the range of $(0,1)$ and the social tie strength is evaluated by the maximum weight between source i and request device j over any possible path in set $\mathcal{P}_{ij}$ in the social network graph G. Thus, the larger the social tie strength, the lower the coefficient, and the less the negative impact of transmission energy consumption on the source's valuation. Then, we can obtain a strict preference order of source i that $\forall j_1, j_2 \in R$, $j_1 \succ_i j_2$ if and only if $u_{ij_1} > u_{ij_2}$. Based on the preferences of the request devices and sources, we formulate a stable matching problem. As there are many notions of stability, we consider a widely used stability definition, *i.e.*, two-sided stability, which means a matching is stable if and only if there is no blocking pair that would both prefer each other to their present assignments (*i.e.*, a matched partner or an unassigned state). In our context, suppose that i_1 is matched to j_1, and i_2 is matched to j_2. Then, i_1 and j_2 that are not matched with each other become a blocking pair if and only if $j_2 \succ_{i_1} j_1$ and $i_1 \succ_{j_2} i_2$. In other words, a matching is stable if there does not exist a pair that would prefer to be matched with each other than with their existing respective partners.

To obtain a stable matching between the request devices and sources, we formulate a college admission problem, which is a bipartite many-to-one match-

ing with two-sided preferences. In the college admission problem, there are two sets of players, which are often termed students and colleges. Students apply to colleges and colleges decide whether to accept. Each college has a capacity number which indicates the maximum number of students that it can accept. Students and colleges have preference orders toward the players in the opposite set. Here, we model request devices as students, sources as colleges, and a source's maximum number of transmission messages as the capacity of a college. Then, the problem of coordinating data forwarding between request devices and sources is transformed into a college admission problem.

Next, we use the DAA [61] to solve the college admission problem, which is described in Alg. 8. As seen in Alg. 8, we first construct the preference orders of request devices and sources. Then, Alg. 8 proceeds iteratively with request devices proposing to sources and sources deciding whether to accept proposals. In each iteration, each request device considers the subset of sources toward which it has positive valuations, and proposes to the source that ranks the highest according to its preference order among the sources that it has not proposed to. After all request devices have proposed, every proposed source makes acceptance decision depending on its available capacity and its preference order. Each proposed source ranks the previously accepted requested devices if any and the newly proposing request devices, and then temporarily accepts the top ranked request devices up to its capacity and rejects the remaining request devices. The above procedure keeps iterating

Algorithm 8: The data forwarding process with moneyless incentives based on stable matching.

Input: Source set S, set of request devices R, social network graph G, transmit limits of sources $\{l_i, \forall i \in S\}$
Output: Pairing result $\{x_{ij}, \forall i \in S, j \in R\}$

begin Construct preference orders of request devices and sources
  for *each request device* $j \in R$, *each source* $i \in S$ **do**
    Compute v_{ij} and u_{ij} according to (5.5) and (5.10), respectively
  for *each request device* $j \in R$ **do**
    Obtain candidate sources for device j: $\tilde{C}_j \leftarrow S \cap C_j$ // C_j *is coverage subset of device* j *in Alg. 6*
    Sort sources in $\tilde{C}_j$ in descending order of $v_{ij}, \forall i \in \tilde{C}_j$
begin Derive stable matching between request devices and sources
  $\tilde{R} \leftarrow R$ // $\tilde{R}$ *is set of unmatched request devices*
  while $\tilde{R} \neq \varnothing$ *and* $\exists j \in \tilde{R}$ *with* $\tilde{C}_j \neq \varnothing$ **do**
    Initialize set of request devices proposing to source i: $Q_i \leftarrow \varnothing, \forall i \in S$
    begin Request devices propose to sources
      for *each request device* $j \in \tilde{R}$ *with* $\tilde{C}_j \neq \varnothing$ **do** // *Device* j *has not proposed to all sources*
        Request device j proposes to first source $i \in \tilde{C}_j$, record proposal: $Q_i \leftarrow Q_i \cup j$
        Remove source i from set $\tilde{C}_j$: $\tilde{C}_j \leftarrow \tilde{C}_j \setminus i$ // *Request device* j *has proposed to source* i
    begin Sources make decisions to proposals
      for *each source* $i \in S$ *with* $Q_i \neq \varnothing$ **do**
        Rank already accepted request devices and new proposals in Q_i in descending order of u_{ij}
        Accept at most top l_i request devices (depending on accepted and new proposing candidates), and reject the rest if any
        Remove these accepted request devices from $\tilde{R}$
        Update $x_{ij}, \forall j \in R$, accordingly
Return $\{x_{ij}, \forall i \in S, j \in R\}$

until each request device has been matched to a source or has proposed to every source. The resulting matching is not only two-sided stable without any blocking pair but also optimal for request devices [61].

5.3 Simulation Results

5.3.1 Synthetic Dataset

To evaluate the performance of our proposed mechanisms, we first conduct computer simulations over a synthetic dataset, in which 100 D2D users are uniformly distributed within a 200m $\times$ 200m square region, and the BS is located at the center point of the area. The transmission range of D2D users is set to 100m with a D2D transmit power level of 100mW. The path-loss exponent and noise variance are set to $\alpha = 4$ and $\sigma^2 = 5 \times 10^{-7}$mW, respectively. The carrier bandwidth is set to 200kHz. Each D2D user requests a message randomly from a library of size 6. A user's preference toward each message follows a log-normal distribution [62] in the range of $(0, 1]$, with a mean within $[0.4, 0.6]$ and a variance equal to 1. The size of each message is set to be uniformly distributed in the range of $[5, 9]$MB. The data transmission rate is required to be at least 1MB/s. The maximum number of messages that each D2D device can transmit is set to be uniformly distributed in the range of $[1, 10]$.

In the simulations, we use the classic weighted social network model, the Kumpula model [63], to generate the social relationships between D2D users. The Kumpula model uses several predetermined parameters, and we set the following values: $\Delta t = 1$, $\delta = 0.3$, $w_0 = 1$, $p_\Delta = 0.03$, $p_r = 0.02$, and $p_d = 0.001$. To generate the weighted social network model among 100 D2D users, we run the simulations for 25000 steps. In each step of a time

interval Δt, three schemes are carried out in sequence, including two schemes for creating links, *i.e.*, local attachment and global attachment, and a node deletion scheme.

- In the local attachment scheme, each node i selects one of its neighbours, say, node j, with probability w_{ij}/s_i, where w_{ij} is the weight of the edge between i and j, and $s_i = \sum_j w_{ij}$. If the selected node j has some other neighbours besides i, node j chooses one node (say, k) from these neighbouring nodes except for i with probability $w_{jk}/(s_j - w_{ij})$. If there exists no link between node i and node k, a link with weight w_0 is generated with probability $p_\Delta \Delta t$. If a link between i and k has existed, the current weight is then increased by δ. After that, w_{ij} and w_{jk} are both increased by δ.

- In the global attachment scheme, each node without any link generates a link of weight w_0 to a random node in the network with probability $p_r \Delta t$.

- In the node deletion scheme, each node and its adjacent links are removed with probability $p_d \Delta t$. The deleted node is then replaced by a new node.

The social network generated by the Kumpula model presents desirable topological properties of social networks, such as cyclic closure and focal closure, and it is compatible with the hypothesis of weak links [63]. However, the range of the social tie strengths is very large, varying from one to several

Table 5.2: The normalization model for strengths of social ties.

Category	**Proportion**	**Normalized Strength**
Very weak	0.2	0.25
Weak	0.4	0.5
Strong	0.3	0.75
Very strong	0.1	1

thousand. Hence, we propose a scaling scheme to normalize the strengths of social ties to the range of $[0, 1]$. Inspired by the definitions of weak ties and strong ties in [64,65], we further classify people's social ties into four categories, *i.e.*, *very weak*, *weak*, *strong*, and *very strong*. As shown in Table 5.2, the normalized strengths of social ties in the categories of very weak, weak, strong, and very strong are 0.25, 0.5, 0.75, and 1, respectively. According to estimates of regular people's social tie strengths, we set the proportions of very weak, weak, strong, and very strong ties to 0.2, 0.4, 0.3, and 0.1, respectively. Given the weights of the original social network graph generated by the Kumpula model, we rank them in an ascending order and then regard the top 20% of social ties as very weak, the next 40% as weak, the subsequent 30% as strong, and the bottom 10% as very strong.

5.3.2 Experiment Results with Synthetic Dataset

In this section, we examine the effects of the number of initial sources and the maximum number of transmission messages on our mechanisms, using the synthetic dataset generated by the approach given in Section 5.3.1. In

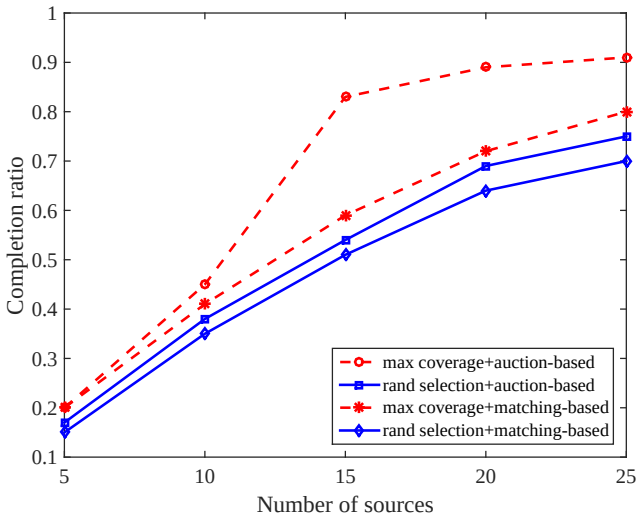
the simulations, we compare our proposed source selection algorithm with a random source selection approach, which randomly chooses a target number of initial sources among the users.

To evaluate the effect of the number of initial sources, we test the cases with 5 to 25 initial sources. The experiment results are based on the averages of 100 runs. Fig. 5.3 shows the completion ratio and total utility with different numbers of initial sources. Here, the completion ratio is the ratio of the users whose message requests are satisfied directly by the BS or indirectly by the selected sources. The total utility is defined as the summation of all users' utilities toward their received messages, given by

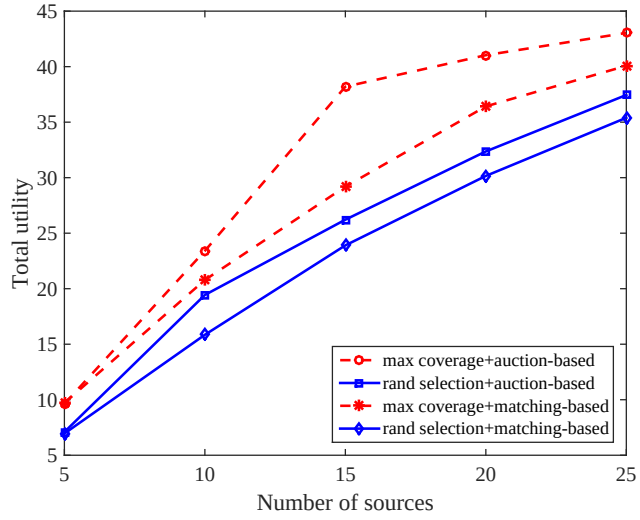
$$\varphi = \sum_{i \in S} \sum_{k \in M} g_{ik} + \sum_{j \in R} \sum_{k \in M} \sum_{i \in S} x_{ij} \cdot g_{jk} \tag{5.11}$$

where the first summation term is the total utility of all sources, while the second term is the total utility of the request devices that are successfully paired with some sources.

As seen in Fig. 5.3(a) and Fig. 5.3(b), with our proposed source selection algorithm based on maximum coverage, both the auction-based monetary mechanism and the matching-based moneyless mechanism achieve higher completion ratio and total utility than the corresponding mechanisms with random source selection. This demonstrates that our proposed source selection approach effectively chooses initial sources for further data forwarding. Also, we can see that, with the proposed source selection approach, the auction-based



(a) Completion ratio.



(b) Total utility.

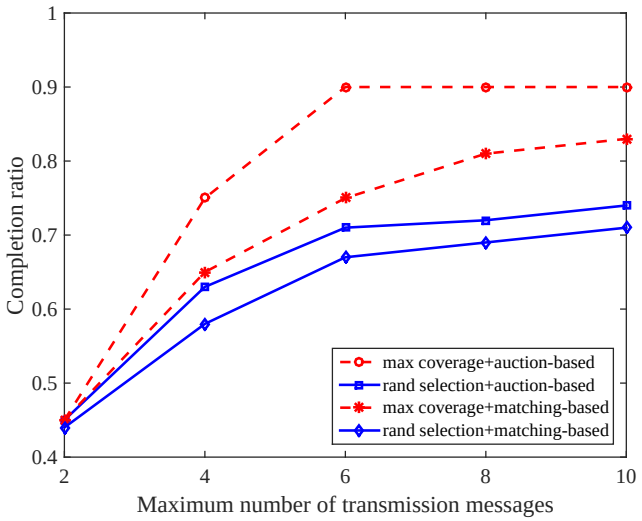
Fig. 5.3: Comparison of data dissemination mechanisms with different numbers of sources with synthetic dataset.

monetary mechanism achieves the highest performance. Although the performance of matching-based moneyless mechanism is lower than that of the auction-based monetary mechanism, it guarantees the stability of the matching results. In addition, it is observed that, with the increase of the number of sources, the performance of both mechanisms first increases rapidly, but then the increase speed slows down gradually. This indicates that the effect of the number of sources on the data dissemination performance becomes less evident when the number is larger than a certain threshold.

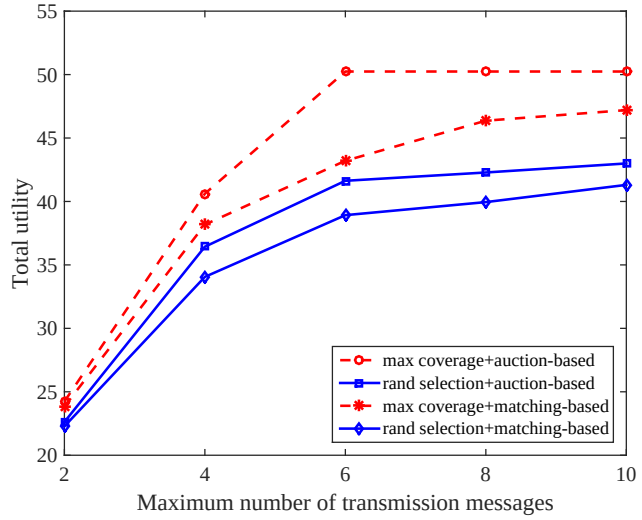
Moreover, we vary the maximum number of transmission messages of sources between 2 and 10 to examine its effect on the data dissemination performance, while the number of initial sources is fixed to 15. Fig. 5.4 shows the completion ratio and total utility with the varying threshold on the maximum number of transmission messages. The results are the averages of 100 runs. As seen in Fig. 5.4(a) and Fig. 5.4(b), the performance varies similarly with the maximum number of transmission messages as with the number of sources in Fig. 5.3(a) and Fig. 5.3(b), respectively. It is also noticed that, when the maximum number of transmission messages exceeds a certain value (*e.g.*, 6 in this experiment), its effect on the data dissemination performance becomes less significant.

5.3.3 Real Tracing Dataset

Moreover, we test our mechanisms with the real tracing dataset, Loc-Brightkite [66]. Loc-Brightkite is a location-based online social network dataset, which



(a) Completion ratio.



(b) Total utility.

Fig. 5.4: Comparison of data dissemination mechanisms with different maximum numbers of transmission messages with synthetic dataset.

records the time and location information (latitude, longitude, and location id) of the check-in activities of 58228 users over the period of April, 2008 to October, 2010, and those users' social relationships. We perform some pre-processing to this dataset before using it in the simulations. We randomly select a day from the time period of the dataset, and select the top 100 users who have the highest number of social ties with others in the set of people that check in on that day. We project these 100 users to a rectangular coordinate system of the size 400 m $\times$ 400 m and with the BS located at the center point. Based on a user's check-in latitude and longitude, the user is projected into one quadrant of the rectangular coordinate system at a random location within the quadrant. For example, if the sign of a user's check-in latitude is negative and the sign of that user's check-in longitude is positive, we place the user at a uniformly distributed location in the second quadrant.

Due to the lack of users' social tie strength information in this dataset, we infer users' social tie strengths as follows. If two users i and j are friends, the initial value of their social tie strength, w_{ij}, is set to 1. Then we further adjust the social tie strength based on the difference of their check-in time at each location where they both appear on the same day during the whole time period of the dataset. Specifically,

$$w_{ij} \leftarrow w_{ij} + \sum_{d \in D} \sum_{h \in H} (1 + \eta_{d,h}) \tag{5.12}$$

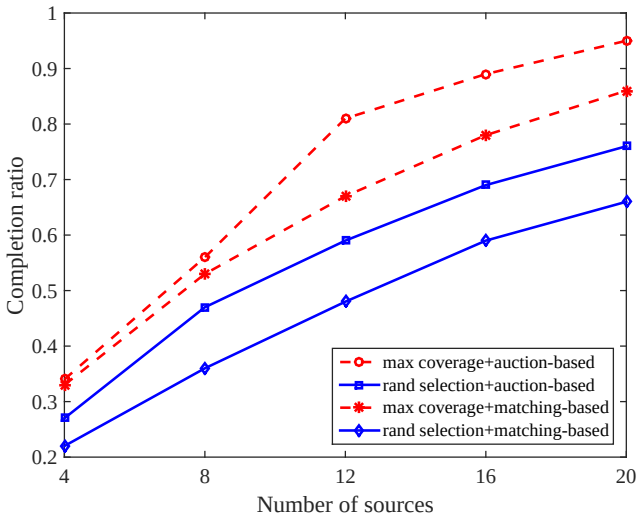
$$\eta_{d,h} = 1 - \frac{|(t_i(d,h) - t_j(d,h)|}{24} \tag{5.13}$$

where D is the set of days for the dataset, H is the set of locations, and $t_i(d,h)$ and $t_j(d,h)$ are the check-in time (in hours) of user i and user j at location h on day d, respectively. Hence, $|(t_i(d,h) - t_j(d,h)|$ is the time difference of their check-in time. Our rationale behind the definition in (5.12) is that two users tend to have a stronger social relationship if they frequently appear at the same location at closer time. Hence, for each time that users i and j are found to show up at the same place on the same day, w_{ij} is increased by $(1 + \eta_{d,h})$, where $\eta_{d,h}$ is inversely proportional to the difference of check-in time on day d at location h. Based on the raw values of the social tie strengths obtained by (5.12), we further normalize them to the range of $[0, 1]$, using the same approach as for the synthetic dataset. The other simulation parameters are set to the same values as in the synthetic dataset.

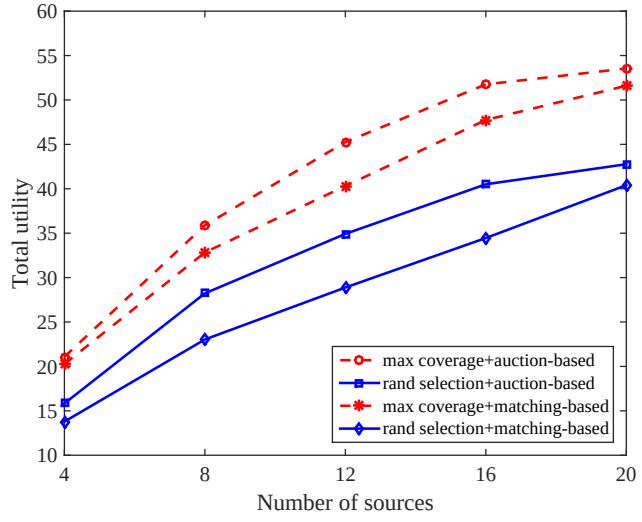
5.3.4 Experiment Results with Real Tracing Dataset

In this section, we use the real tracing dataset preprocessed by the approach described in Section 5.3.3. Similar to the experiments with the synthetic dataset, we vary two parameters, *i.e.*, the number of initial sources and the maximum number of transmission messages, to examine their effects on the completion ratio and the total utility. The experiment results are based on the averages of 100 runs.

Fig. 5.5 shows the completion ratio and total utility when the number of initial source varies between 4 to 20. As seen in Fig. 5.5, our proposed solutions also work well in the real scenarios. Compared to the random source selec-



(a) Completion ratio.

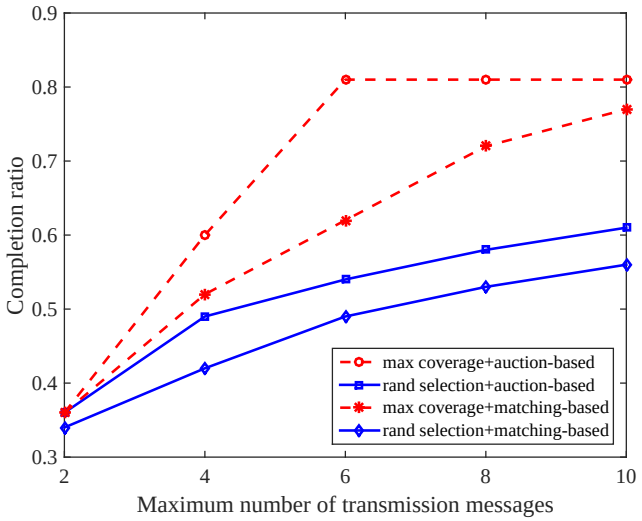


(b) Total utility.

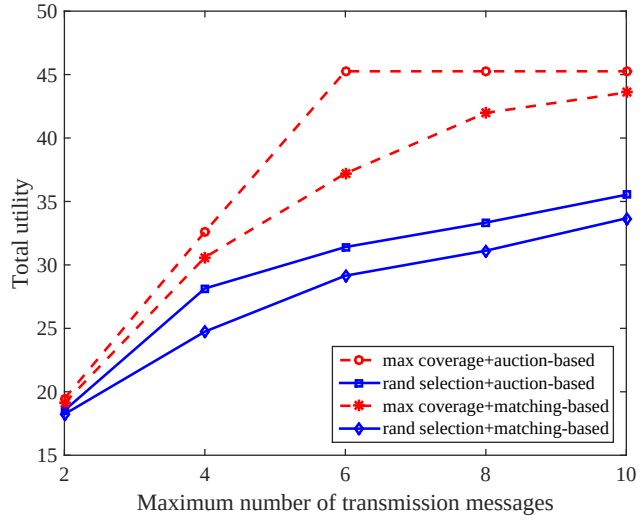
Fig. 5.5: Comparison of data dissemination mechanisms with different numbers of sources with real tracing dataset.

tion approach, our proposed algorithm performs more efficiently in choosing high-quality sources. Moreover, it is observed that both the auction-based monetary mechanism and the matching-based moneyless mechanism achieve good performance. In addition, we can see that the performance gap of the respective mechanisms with the real tracing dataset becomes larger than that with the synthetic dataset. With the real tracing dataset, the data forwarding mechanisms need fewer initial sources to achieve nearly the same performance when the corresponding mechanisms are applied to the synthetic dataset. This is because the real tracing dataset contains denser social connections among the users and people with social ties are located in a relatively nearby region.

Furthermore, we vary the maximum number of transmission messages by each selected source from 2 to 10 and fix the number of selected sources to 12. We run 100 experiments for each case to obtain an average result. Fig. 5.6 shows the completion ratio and the total utility with different maximum numbers of transmission messages. As seen in Fig. 5.6, the transmission message limitation shows a similar effect as with the synthetic dataset. Also, due to denser deployment and social connections of users in the real tracing dataset, Fig. 5.6 presents larger performance gaps between different approaches as compared with the results in Fig. 5.4.



(a) Completion ratio.



(b) Total utility.

Fig. 5.6: Comparison of data dissemination mechanisms with different maximum numbers of transmission messages with real tracing dataset.

5.4 Summary

In this chapter, we propose a social community based data dissemination scheme via D2D communications. Our scheme aims at maximally satisfying target users' preferences for messages and exploits weighted social relationships, which can be direct or indirect links between any two users in a connected community. A comprehensive solution is proposed to choose initial sources and direct subsequent data forwarding via D2D communications. In the initial source selection, our approach chooses a target number of sources with the maximum potential coverage effects. In the subsequent data forwarding, we propose a monetary auction-based mechanism and a moneyless matching-based mechanism to incentivize the sources to forward messages for remaining users. The monetary mechanism obtains the global optimal solution and achieves truthfulness, while the moneyless mechanism guarantees two-sided stability with a lightweight implementation. The monetary and moneyless mechanisms can be adopted respectively depending on the practical application scenario. We conduct extensive simulations with both synthetic datasets and real tracing datasets to evaluate the performance of the proposed approaches. In particular, we propose a novel scheme to normalize the strengths of social ties into four categories, and another new scheme to infer strengths of social ties from users' contact information. The simulation results demonstrate the effectiveness of our proposed approaches and effects of various system parameters.

Chapter 6

Social-physical Graph Based Data Dissemination

In Chapter 3 - Chapter 5, we focus on the relatively static scenario in which users' positions are stable in a short time period. The proposed data dissemination schemes can be periodically executed to accommodate the mobility of users. These approaches are based on a two-phase procedure, which includes initial seed selection and subsequent data forwarding. In this chapter, we further integrate opportunistic contacts with user mobility into the data dissemination schemes while considering users' behaviour characteristics and incentives. We propose a three-phase approach for data dissemination in MSNs, 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. We apply a graph partitioning approach to divide the social-physical graph into several tightly-knit communities, and then leverage a centrality measure to select central nodes in the generated communities as seeds. After that, it follows with Phase II and Phase III for 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. As such, data can be more effectively disseminated to users with fewer social connections or opportunistic contacts due to mobility. The theoretical analysis for the message selection mechanism proves its truthfulness. Extensive simulation results further demonstrate the effectiveness of the proposed three-phase approach with various synthetic and real tracing datasets. Table 6.1 lists the symbols used in this chapter.

6.1 System Model

Here, we consider a data dissemination scenario depicted in Fig. 3.1 of Chapter 3, 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 to them, and then the seeds and any receiving user further forward the data to others via D2D communications underlaying the cellular network.

Table 6.1: Symbols for Chapter 6.

Symbol	Definition
M	Set of messages to be disseminated to users
N	Set of target users in an area for data dissemination
v_{ik}	Valuation (utility) of user i for message k
D	Set of seeds
G_0	Social graph modeling social ties among users
$e = (i, j)$	Representing users i and j are socially connnected
τ	Length of one time slot
T	Time frame
p_{ij}	Contact probability that node i and node j have at least one encounter within a time frame
G	Social-physical graph
σ_{sd}	Number of shortest paths from node s to node d
$\sigma_{sd}(e)$	Number of shortest paths from node s to node d that pass through edge e
d_{sd}	Length of the shortest path from node s to node d
c	Number of communities
g	Maximum number of messages that ego node can send in one dissemination period
δ_{ik}	Representing whether node i misses message k
y_s	A randomly generated session key
M_i	Set of messages that node i holds
$\overline{v}_{u_r}\|(u_s, u_d)$	Node u_r's expected valuation toward the pair (u_s, u_d)
$\overline{v}_{(u_s,u_d)}\|u_r$	Pair (u_s, u_d)'s expected valuation toward node u_r
$N^{'}$	Set of orphan nodes
$E^{'}$	Set of directional edges (socially connected pairs)
θ	Threshold percentage of messages that a node receives in dissemination
$E_r^{'}$	Directional edges in orphan node u_r's acceptable set

6.1.1 Social Graph Model

Considering the popularity of various social media, a social graph can be obtained from online social network platforms such as Facebook, Twitter, LinkedIn, Sina Weibo, and WeChat. Letting N denote a set of users in the system, we use an unweighted and undirected social graph $G_0(N, E)$ to model the social ties among the users in N, where an edge $e = (i, j) \in E$ represents that nodes i and j are socially connected via social relationships, such as among family members, friends, colleagues, collaborators, *etc.* Social trust is a key social phenomenon among socially connected people, while altruistic behaviors are observed among people with social trust in many human activities [67,68]. That is, people are motivated to adopt a generous action that benefits their social contacts at their own costs. Therefore, a user is willing to expend its resources and share data with other users with social connections. Hence, an edge in the social graph G_0 captures the existence of social trust between the corresponding users that incentivizes them to disseminate data toward each other.

6.1.2 Physical Network Model

The physical network supporting data dissemination needs to be characterized by the transmission and contact processes among nodes. While the transmission feasibility in the mobile network 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 [69], 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 distribution or a Pareto distribution. The *contact duration* is modeled by a uniform distribution [70]. 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}.

6.2 Three-Phase Solution

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. Basically, there are two classes of incentives: monetary and moneyless. Monetary incentives involve transfer of money or virtual currency. That is, a forwarding node is rewarded money to compensate for its cost of resources in data forwarding. In contrast, moneyless incentives are often used in the environments where monetary compensation is difficult (*e.g.*, due to security concern with online payment) or prohibited (*e.g.*, for ethical or legal reasons).

As argued in [32,68], the existence of social trust between two socially connected users justifies 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, i.e., *social incentive*. Moneyless incentives have been considered in cooperative communications, where a relay node helping a source-destination pair can be allocated higher transmit power or higher priority for channel access. There are also studies that group two [71] or more nodes [68] into a coalition, so that they can mutually benefit from relaying for each other and thereby remain in a stable structure. We refer to this form of moneyless incentives with exchange of resources (*e.g.*, transmit power) or services (*e.g.*, relaying) as *cooperative incentive*.

To accommodate the incentive constraint, we consider a three-phase approach as illustrated in Fig. 6.1. Similar to the existing two-phase approach, Phase I selects initial seeds such that the BS first dispatches the messages to the seeds. Differently, we take into account the social-physical graph given in Section 6.2.1. Further, we split the subsequent data forwarding into Phase II and Phase III among socially connected users and among cooperative users, respectively. The two phases of data forwarding properly address social incentive and cooperative incentive, respectively.

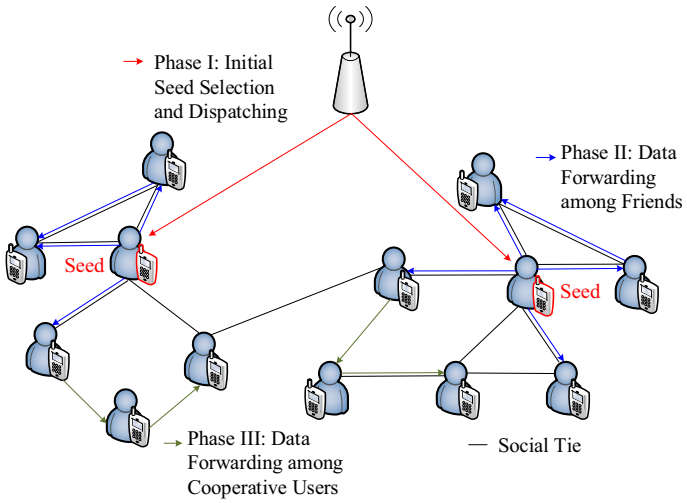


Fig. 6.1: The three-phase data dissemination approach.

6.2.1 Phase I: Initial Seed Selection and Message Dispatching

The social and physical aspects have been jointly considered in previous works such as [68,72] for cooperative relaying and information diffusion, respectively. In this work, we specify the joint social-physical connection in our unique fashion and apply it to an opportunistic data dissemination scenario with the incentive constraint. To assimilate the social and physical aspects of the system, we couple the social graph G_0 and the physical network model to derive a *weighted* and undirected social-physical graph G. Graph G inherits the node set and edge set from G_0 and further labels each edge $e = (i, j) \in E$ by a length metric

$$\text{length}(e) = \log \frac{1}{p_{ij}}. \tag{6.1}$$

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. Betweenness of a vertex or an edge is the sum of the fraction of the shortest paths between each pair of vertices that pass through the vertex or edge in question. Here, we consider *edge-betweenness* defined by

$$\text{betweenness}(e) = \sum_{s,d \in N, e \in E} \frac{\sigma_{sd}(e)}{\sigma_{sd}} \tag{6.2}$$

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. A high edge-betweenness implies that an edge behaves like a bridge connector between two sections of a graph, and its removal may impede communication between the nodes in the two sections [73]. Given the length metric in (6.1), the total length of a path from node s to node d is given by

$$\text{length}(P) = \log \frac{1}{\prod_{e=(i,j) \in P} p_{ij}} \tag{6.3}$$

which actually indicates the "*transmissibility*" [72] of information from node s to node d, since the product term gives the probability that information spreading potentially happens over each link of the path.

Closeness of a vertex is defined by

$$\text{closeness}(s) = \frac{1}{\sum_{s,d \in N, s \neq d} d_{sd}} \tag{6.4}$$

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 [74]. As the social-physical graph may not be fully connected, *harmonic centrality* [75] in the following is used instead:

$$\text{closeness}(s) = \sum_{s,d \in N, s \neq d} \frac{1}{d_{sd}}. \tag{6.5}$$

Based on the social-physical graph G, we can perform social-aware community construction and corresponding seed selection for this phase. The basic idea is to first partition graph G into c densely connected subgraphs, *i.e.*, communities, by iteratively removing edges that act like bridges linking different sections of the graph. Then for each generated community, the selected seed is the node which can spread data at the highest speed to other nodes in this community.

Specifically, we use the Girvan-Newman algorithm [76] based on the edge-betweenness defined in (6.2) to partition the social-physical graph into c communities, as illustrated in Fig. 6.2. The key idea of the Girvan-Newman algorithm is to remove the edge of the highest betweenness (break a tie

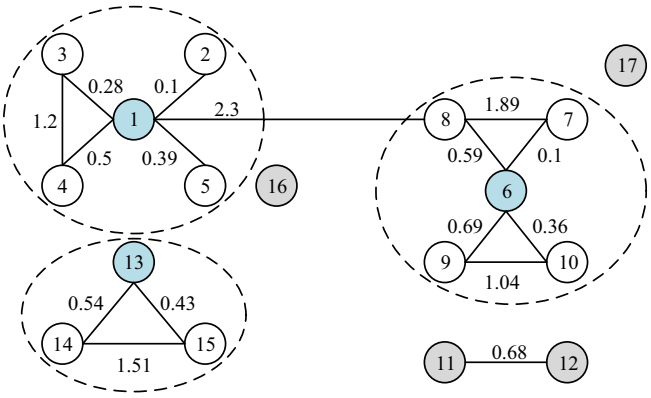


Fig. 6.2: Partitions of social-physical graph for community formation and seed selection. Here, three nodes (1, 6, and 13) are selected for three reasonably large communities. Nodes (11, 12, 16, and 17) are not connected to any seed and have to leverage cooperative means to receive messages in dissemination.

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. Thereby, the nodes within each community are more strongly connected than those in the rest of the communities. After the graph partitioning, we further evaluate the vertex-closeness of each node according to the definition in (6.5). Here, the calculation of closeness depends on the local community structure instead of the original social-physical graph. For each community, the node of the highest closeness is then selected as a seed. Note that the number of seeds can be limited by adjusting the minimum size of communities. Since more seeds improve the dissemination speed but also cost more resources of the BS, we need to achieve a good balance between the dissemination speed and

resource cost of the BS.

6.2.2 Phase II: Data Forwarding Among Socially Connected Users

Due to the dynamic and autonomous nature in D2D data forwarding, a decentralized solution is more feasible in practice. Hence, Phase II focuses on data forwarding from the perspectives of individual nodes. Any node that receives some messages automatically becomes an *ego node* and when active spreads out its available messages to its socially connected nodes (for simplicity, generally referred to as "friends" in the following) within the D2D communication range. At the beginning of Phase II, the initial seeds selected in Phase I first become ego nodes and ready for further dissemination. After that, any node that receives some messages also turns into an ego node and disseminates messages toward its friend nodes. To improve energy efficiency, we assume that each ego node is only periodically activated for dissemination according to a certain schedule. In view of user mobility and availability, a user's friends may not be always active or stay in the close proximity. Some friend nodes may move away while others may come up. Therefore, at the beginning of an active period, an ego node first performs peer discovery, *e.g.*, by broadcasting a probing signal, to identify its friends within the D2D communication range. Then, the ego node sends a catalog of available messages in possession to the friend nodes that echo its probing. 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.

Fig. 6.3 illustrates a concrete example, where an ego node has 6 messages $\{m_1, m_2, ..., m_6\}$ available and 4 active friend nodes $\{u_1, u_2, u_3, u_4\}$ within its D2D transmission range. Here, u_1 is missing messages $\{m_1, m_3, m_4\}$ and quantifies its valuation toward these messages as 0.9, 0.3, and 0.16, respectively. The other nodes $\{u_2, u_3, u_4\}$ have different preferences on the messages. This situation can also be abstracted as a bipartite graph in Fig. 6.4. 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. Then, the ego node needs to choose at most g messages on the right side to maximize the total valuation of the edges incident on the selected messages.

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. We refer to this as an *efficiency* requirement. This looks similar to a maximum weight bipartite matching (MWBM) problem formulated in [77,78], between a set of objects and a sequence of broadcast time slots to determine an optimal forwarding schedule. Nonetheless, we consider a many-to-one matching rather than a one-to-one matching in MWBM. This is because a multicast message will potentially benefit multiple nodes which are expecting

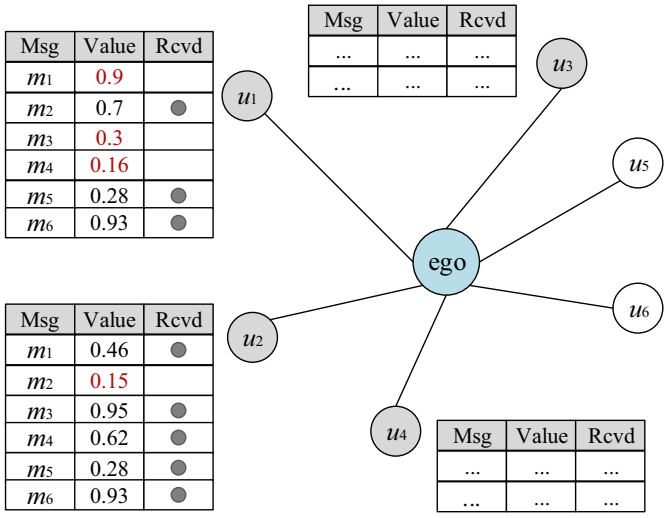


Fig. 6.3: Data forwarding among friend nodes. In this example, $\{u_1, u_2, u_3, u_4\}$ are in contact with the ego node, while $\{u_5, u_6\}$ are out of the D2D communication range.

it. Moreover, the number of selected messages for matching is upper-bounded to accommodate the energy constraint.

Second, we want to address the strategic behavior of the receiving nodes. As illustrated in Fig. 6.3, each friend node on the left has its private preference toward the available messages on the right, which is only known to the friend node itself and needs to be solicited by the ego node. To maximize the receiving nodes' total utility with the selected messages, it is crucial to ensure that each friend node submits a *truthful* report consistent with its private information.

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 receiv-

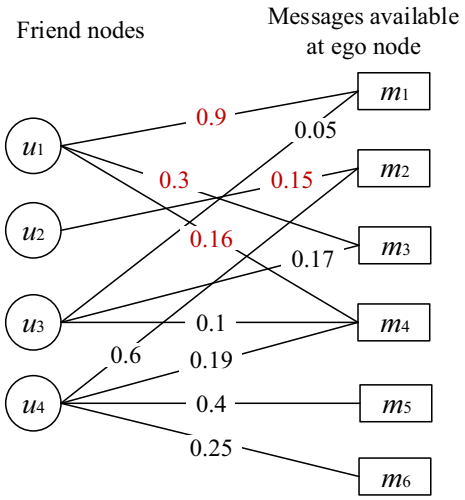


Fig. 6.4: Message selection modeled by a bipartite graph.

ing nodes. According to the *strong triadic closure* property [79] of social networks, if node A is connected to nodes B and C with *strong ties*, it is likely that nodes 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 there is lack of social trust among the receiving nodes.

Without social trust among each other, a receiving node can lie about its private preference toward the available messages to maximize its own payoff. Since the ego node integrates the preferences of all receiving nodes and selects certain messages to maximize the overall utility, a receiving node may lie to the ego node its preference toward the messages such that its most preferred messages are selected. Such untruthful strategic behavior is detri-

Algorithm 9: 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: $S \subseteq M = \{m_k : x_k = 1, 1 \leq k \leq m\}$, $x_k \in \{0, 1\}$

```
x_k = 0, ∀1 ≤ k ≤ m                    // Initialize message selection
S ← ∅
m' ← number of messages with positive total values
if m ≤ g then
    begin Select all messages for which an interest exists
        x_k = 1, if Σ_{i=1}^{n} δ_ik v_ik > 0, ∀1 ≤ k ≤ m
        Return S
ℓ ← 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) ∈ L in the above order do
    if ℓ = min{g, m'} then
        break                          // No more message is available or allowed
    if x_k = 0 then
        x_k ← 1                        // Add the newly incident message
        S ← S ∪ {m_k}
        ℓ ← ℓ + 1
Return S
```

mental because the untruthful declaration leads to a nonoptimal and even unpredictable solution. Therefore, we require a truthful mechanism which incentivizes the receiving nodes to report their true preferences. A truthful mechanism ensures that a receiving node maximizes its payoff by revealing its true preferences, regardless of other receiving nodes' reports. Then, there is no incentive for the receiving node to submit an untruthful report.

As in [80], we assume that all possible, 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. 9. 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. 9 gives a truthful mechanism.

Theorem 1. *The mechanism based on Alg. 9 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. 9. 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. Fig. 6.5 shows a simple example to facilitate understanding. In this example, $S = \{m_1, m_2, m_5, m_3\}$ and $\hat{S} = \{m_1, m_5, m_3, m_6\}$. The unique messages m_2

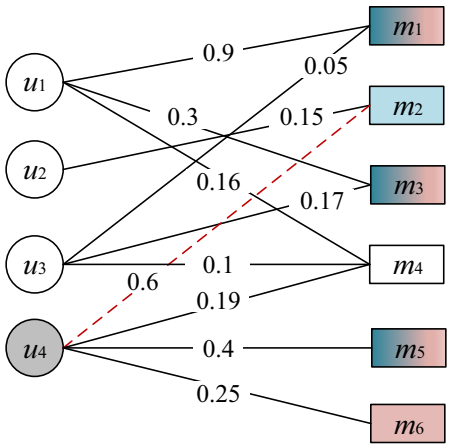


Fig. 6.5: An example illustrating difference between truthful and untruthful reports. Here, $g = 4$ messages are selected at most. When node u_4 hides its edge to m_2, it results in message selection from $\{m_1, m_2, m_5, m_3\}$ with truthful report to $\{m_1, m_5, m_3, m_6\}$ with untruthful report.

and m_6 are paired. This can be interpreted as the misreporting of u_i leads to a switch of selection from m_2 to m_6.

Here, we notice one important observation which is key to the proof of truthfulness. 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. Because Alg. 9 selects messages in a non-increasing order of v_{ik}'s, 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.

□

6.2.3 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. This one-hop incentive-compliant data dissemination is resilient to network dynamics arising from node mobility and availability, since such a decentralized approach only relies on each node's local information, which can be easily acquired and updated. Nevertheless, the data dissemination result through Phase II itself may be insufficient. It is possible that even after time W ($W < T$), some node has not received any dissemination message as it has not had a chance to encounter its friends. In addition, as seen in Fig. 6.2, 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.

On the other hand, multi-hop scheduling for the data forwarding is potentially more efficient, but it is more difficult to construct a multi-hop path in which every intermediate node is a friend of the receiving node to satisfy the social incentive constraint. Besides, a multi-hop path induces higher uncertainty and recovering cost in case that the dissemination through any intermediate node fails. To balance between resilience and efficiency, we include Phase III to expand the coverage of data dissemination beyond one

hop but still within a manageable scope. In particular, we enable cooperation that mutually benefits both orphan nodes and socially connected nodes.

Consider the scenario illustrated in Fig. 6.6. Here, u_α and u_β are two socially connected nodes, while u_γ is an orphan node. Suppose u_α wants to disseminate the messages in its possession to its friend u_β but cannot 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 disseminate its messages to this stranger node. If u_γ finally 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 cooperative forwarding is in line with the principle of social reciprocity discussed in [68]. A major difference is that we limit the size of reciprocal coalitions to be more robust to opportunistic contacts. The two socially connected nodes actually correspond to an edge in the social-physical graph G. If we consider the two friend nodes as one entity, the grouping of reciprocal coalitions becomes a bipartite matching problem. As shown in Fig. 6.7, the left side is the set of orphan nodes $N' \subset N$. The right side is the set of *directional* edges, denoted by E'. For each edge $(u_s, u_d) \in E$, two entities,

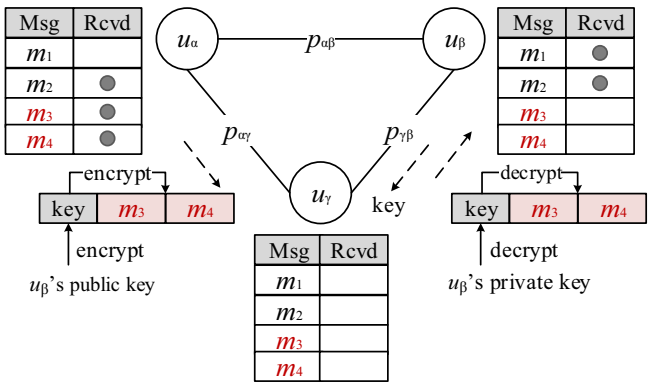


Fig. 6.6: Data forwarding among an orphan node u_γ and two socially connected nodes (u_α, u_β).

(u_s, u_d) and (u_d, u_s), are included in E' for both directions.

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

$$\overline{v}_{u_r}|(u_s, u_d) = p_{sr} \cdot p_{rd} \sum_{m_k \in M_s \cap \overline{M}_r \cap \overline{M}_d} v_{rk}. \tag{6.6}$$

As seen, u_r's valuation depends on its contact probabilities with u_s and u_d, and its utility from the messages that are available at u_s and demanded by

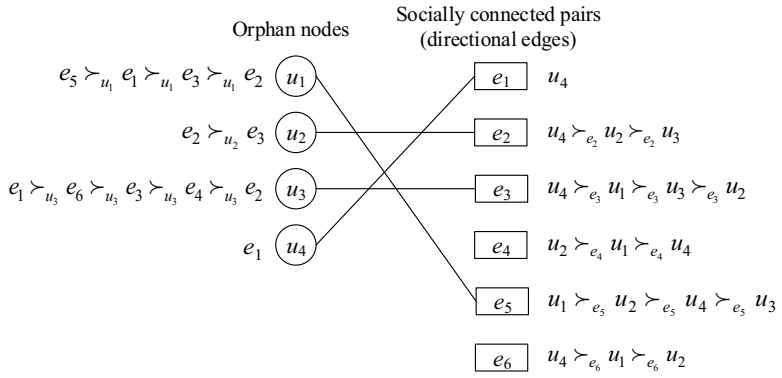


Fig. 6.7: A cooperation pairing example modeled as a stable matching problem with a bipartite graph.

both u_r and u_d. Similarly, the preference of (u_s, u_d) over u_r can be measured by

$$\overline{v}_{(u_s,u_d)}|u_r = p_{sr} \cdot p_{rd} \sum_{m_k \in M_s \cap \overline{M}_r \cap \overline{M}_d} v_{dk}. \tag{6.7}$$

Based on the definition in (6.6), 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 (6.7), 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' as illustrated in Fig. 6.7, such that *both sides* are satisfied with the matching. This can be formulated as the stable matching problem (a.k.a. the stable marriage problem) [61]. A matching is said to be (two-sided) stable if and

only if there is no blocking pair which would *both* prefer each other to their present assignments (*i.e.*, a matched partner or an unassigned state). In our context, suppose u_{r_1} is matched to e_1 and e_2 is matched to u_{r_2}. Then u_{r_1} and e_2 which are not matched become a blocking pair if and only if $e_2 \succ_{u_{r_1}} e_1$ *and* $u_{r_1} \succ_{e_2} u_{r_2}$.

Gale and Shapley proved in [61] that a stable matching always exists and propose the DAA to find a stable matching which is optimal to the proposing side. The stable matching problem originally focuses on an equal number of agents on both sides and a complete preference list for each agent. Here, we actually consider a variant with unequal sets and partial preference lists. The agents excluded from a preference list are often called *blacklisted* or *unacceptable*. Based on the conclusion that all stable matchings engage exactly the same sets of left and right agents, DAA is extended in [81] to address unequal sets. Note that the extended version needs to be slightly modified to accommodate partial preference lists. If there are fewer nodes on the left (n_l) than the right (n_r) and the left side proposes, the algorithm cannot terminate when all right agents have been proposed to. Due to the existence of unacceptable choices, the algorithm can only stop when each proposing agent is either assigned a partner or has exhausted all candidates in its acceptable set.

Last, we need to address the incentive constraint before applying DAA to determine a stable matching. In Fig. 6.7, clearly, there is no social trust between the two sides or among the orphan nodes on the left, though some

entities on the right possibly involve friend nodes. Because the preference order of each entity is private information, it is preferable to use a stable matching mechanism in which each entity on both sides is incentivized to report its preference truthfully. The stability and truthfulness requirements for both sides are stronger than the single-sided requirements for message selection in Fig. 6.4 where the ego node is unselfish toward its friend nodes on the left. However, it was shown in [82] that no stable matching mechanism is truthful for both sides. Since DAA produces a stable matching optimal to the proposing side, when the proposed side behaves honestly, the proposing side has no incentive to misreport their preferences.

Further, it is found in [83] that in an *unbalanced* (*i.e.*, $n_l \neq n_r$) random matching market with complete preference lists, even a slight imbalance can cause the core (*i.e.*, the set of stable matchings) to collapse. In a typical realization, almost all agents have a unique stable partner, and each agent has almost the same average rank of assigned partners under all stable matchings. Particularly, for any $\epsilon > 0$, when the imbalance is sufficiently large, it is an ϵ-Bayes-Nash equilibrium for *all* agents to report truthfully. Moreover, we show in Fig. 6.8 that, even with $n_l = n_r$, the restricted preference lists also induce imbalance and leave little manipulation scope for the proposed side. Here, we control the size of incomplete preference lists using a ratio of the number of unacceptable choices of each agent to the size of a complete list. The double Y-axes show the size of the set of stable matchings and the average fraction of agents with more than one unique stable partner. As

seen, when 30% of the preference lists are unacceptable choices, the fraction of multi-partner agents in stable matchings quickly drops below 0.1, and the number of stable matchings is less than 2 on average. This implies that the restricted preferences also collapse the core similar to imbalance when the unacceptable ratio is sufficiently large, thus allowing little room for agents to gain from untruthful reports.

After Phase II when it comes to cooperative pairing in Phase III, it is likely that the number of orphan nodes in N' is much fewer than that of directional edges in E'. Even if there are an equal number of nodes on both sides of the bipartite graph in Fig. 6.7, each user often holds a different subset of the messages and thus a partial preference list. Complementing the conclusion in [83] with our observation in Fig. 6.8, we are confident that it is reasonable to apply the extended DAA to the cooperative pairing problem while accommodating the incentive constraint.

As given in Alg. 10, 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 can be translated to the agent's preference ordering. Then, letting the candidate nodes propose, we apply DAA to produce a stable matching between N' and E'. Note that the termination condition is slightly modified to accommodate

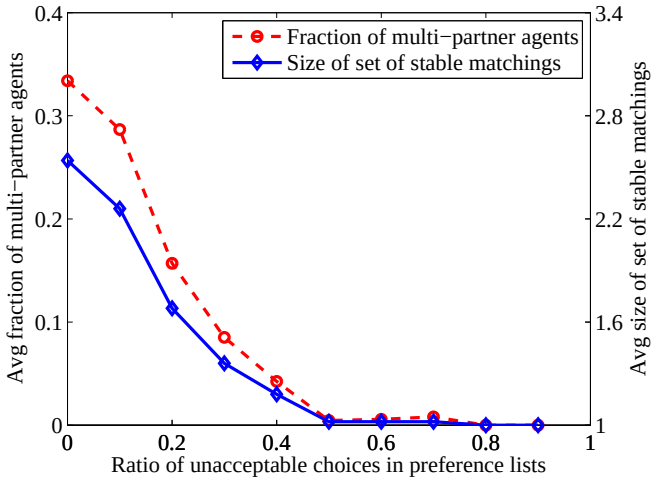


Fig. 6.8: Properties of stable matchings with $n = m = 10$.

unequal sets and restricted preferences.

6.3 Simulation Results

6.3.1 Synthetic Datasets

To evaluate the performance of our proposed mechanisms, we first 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 in the range of $[0.1, 1]$. 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* [51], to generate the social relationships for the remaining 28 users. The caveman model starts with c' isolated complete

Algorithm 10: 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 2 directional edges in E'*
$N' \leftarrow$ nodes in N with 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*
    Do depth-first-search from u_s, and label traversed vertices as visited
$N' \leftarrow N' \cup$ 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**
    begin 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*
stop $\leftarrow$ `false`
begin Terminate when a stable matching between N' and E' via extended DAA
    while stop = *`false`* **do**
        begin Let each node in N' propose to its acceptable choices in E'
            for *all* $u_i \in N'$ **do**
                u_i proposes its most favorable choice, $e_{j^*} = \text{argmax}_{e_j} \overline{v}_{ij}^{(A)}$
                e_{j^*} accepts u_i if $u_i \in B_{j^*}$ and $\overline{v}_{j^*i}^{(B)} > \overline{v}_{j^*i^*}^{(B)}$, and rejects u_i otherwise, where u_{i^*} is e_{j^*}'s present assignment, assuming $\overline{v}_{j^*i^*}^{(B)} = 0$ if $u_{i^*} = \varnothing$
            if *each $u_i \in N'$ is either assigned some $e_j \in E'$ or rejected by all candidates in A_i* **then**
                stop $\leftarrow$ `true`

graphs, also known as *caves*, in which every vertex is adjacent to every other vertex. Then in a rewiring stage, every edge of a cave in the original network is randomly rewired by pointing to a node in another cave with probability p. The rewiring procedure intends to establish random inter-connections between individual nodes of different caves. It has been proved in [51] 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 [70] and average encounter duration is in the range of $[3, 6]$. Users' intercontact duration is assumed to follow a heavy-tailed Weibull distribution [69] 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.

6.3.2 Average Utility / Completion Ratio vs. Time

In this subsection, we compare our truthful mechanisms with the 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 [84] to obtain the optimal solution to the 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 ad-

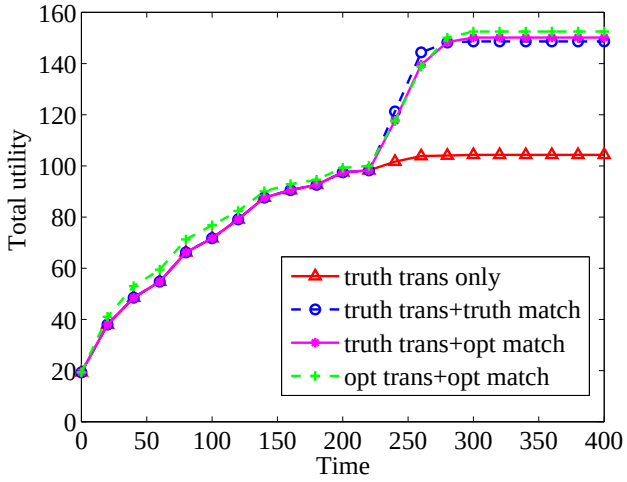


Fig. 6.9: Users' total utility over time.

jacent 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. 6.9 shows users' total utility over time. As seen, high user utility is achieved with the two phases of data forwarding. Compared with only carrying out Phase II throughout the entire process, combining Phase II and Phase III can effectively improve users' total utility. As seen in Fig. 6.9, the total utility of $S_{\texttt{ALG}}$ in Phase II is relatively close to that of $S_{\texttt{OPT}}$. Moreover, with the execution of Phase III, the total utility of our truthful mechanisms is fairly close to that of the corresponding optimal algorithms.

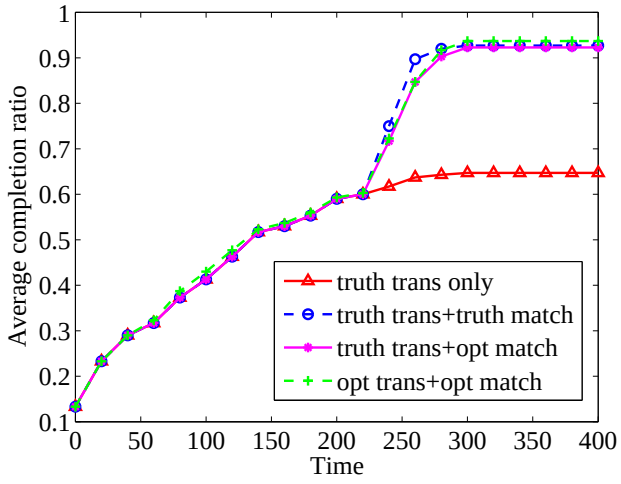


Fig. 6.10: Users' average completion ratio over time.

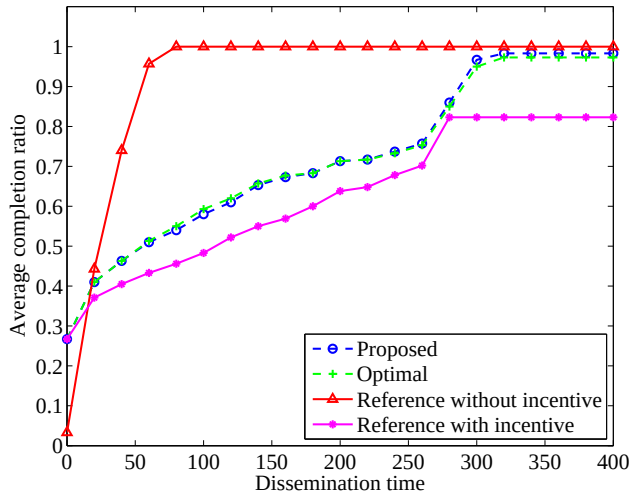
Fig. 6.10 presents users' average completion ratio over time. Similar to Fig. 6.9, Fig. 6.10 shows that our mechanisms achieve a high completion ratio with Phase II and Phase III together, and the optimal algorithms are slightly better than our mechanisms.

6.3.3 Latency Performance

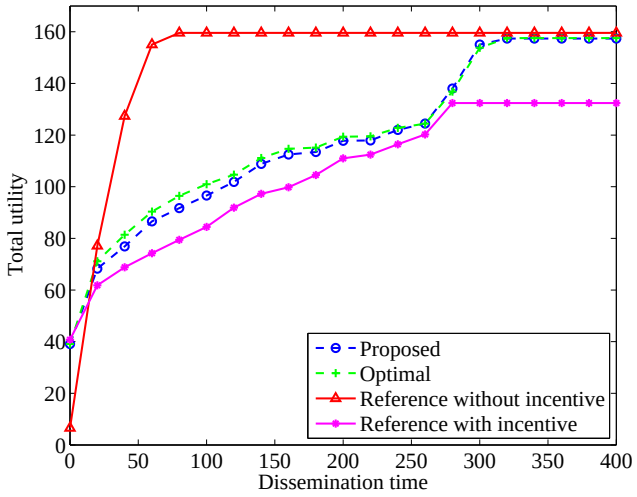
In Section 6.3.2, we have compared our approach with the corresponding optimal solution. In this subsection, we further consider a related work [2], which proposes a novel and inspiring community-based scheme for opportunistic data dissemination. The key idea of this reference scheme is to select nodes belonging to disjoint communities as initial sources, such that the seeds in different communities can propagate the data object in parallel to reduce the dissemination latency. This scheme first ranks the nodes in a descend-

ing order of the summation of its contact frequency to others. According to the ranking, each node is sequentially considered as a seed to construct a community that covers the nodes reachable from the seed through multi-hop forwarding within a deadline. This procedure continues until every node is covered by a community. Different from [2], our approach first constructs communities and then selects seeds. For community construction, we form a social-physical graph and use the Girvan-Newman algorithm to partition the graph into communities based on edge-betweenness. After that, we select the node of the highest vertex-closeness in each community as a seed. In addition, we consider multiple dissemination messages, which induces the message selection problem.

Fig. 6.11 compares the performance of our approach, the scheme proposed in [2], and the optimal solution. As the scheme in [2] involves randomness in forwarding, we run the scheme for 100 times to obtain an average for each case. In [2], it is assumed that any user who already receives the data object can help distribute it to other users through opportunistic transmission. That is, it does not take into account user incentive. Hence, we consider two variants of this reference scheme with or without social incentive. With social incentive, a user is only willing to disseminate data to its socially connected users rather than anyone. Accordingly, we adapt the ranking of sources and community construction by counting only users with social connections. As such, the scheme is protected from performance degradation to accommodate social incentive.



(a)



(b)

Fig. 6.11: Performance comparison of our proposed approach, the community-based scheme in [2], and the optimal solution.

Here, the simulation settings are similar to those in Section 6.3.2, except that Phase III starts at 260, and the number of seeds is set to 8 when social incentive is satisfied. The dissemination deadline is set at 400. When social incentive is neglected in the reference scheme, one seed is sufficient to cover every user. As shown in Fig. 6.11(a), when the incentive constraint is relaxed in the reference scheme, it starts with one seed and spreads data very fast since a user distributes the object to any encountered user. The dissemination latency is around 100 time slots when the completion ratio reaches 100%. In contrast, the dissemination process is slowed down to meet the incentive constraint. As seen, it takes about 110 time slots for our truthful mechanism and the optimal approach to achieve a completion ratio of 60%, while it takes 180 time slots in the reference scheme with the incentive constraint. In addition, the incentive constraint bounds the completion ratio of this reference variant by 82.3% when the dissemination scope is limited by social connections. On the other hand, when our proposed approach further includes cooperative forwarding in Phase III, we can expand the data spreading coverage. As seen in Fig. 6.11(a), it takes 320 time slots in total for our approach to attain a completion ratio of 97.3%. Though the incentive constraint causes extra overhead, our approach can successfully address the challenge and achieve satisfactory performance.

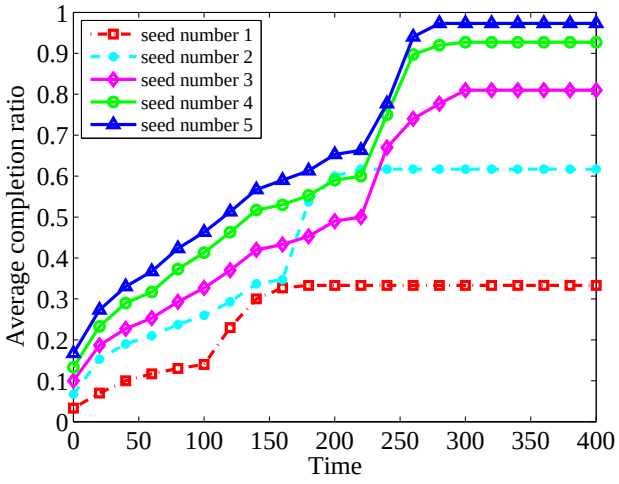


Fig. 6.12: Average completion ratio for different numbers of seeds.

6.3.4 Effect of Number of Seeds

In this subsection, we examine the effect of the number of seeds on our mechanisms. The simulation is also carried out with the previous synthetic datasets and the cases with 1 to 5 seeds are tested respectively. 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. 6.12 shows the results of average completion ratio with different numbers of seeds. As seen in Fig. 6.12, 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.

6.3.5 Performance with Real Tracing Datasets

In this subsection, we test our mechanisms with the real tracing datasets, `Infocom06` [85] and `Sigcomm09` [86]. The trace `Infocom06` records Bluetooth contacts between iMotes distributed to 78 users who attended the conference IEEE INFOCOM 2006 for several days. The trace `Sigcomm09` records the encounter information among 76 participants who carried HTC S620 smartphones with the pre-installed application, MobiClique, for a few days in the conference ACM SIGCOMM 2009. Because of the limitations of these real tracing datasets, we perform some preprocessing to these datasets before using them in the simulations. As for the trace `Infocom06`, no explicit social relationships are given. Here, we infer users' social relationships based on their total contact duration. Two users are considered to be friends if their total contact duration is not less than 18000s. For the trace `Sigcomm09`, contact duration is not given for each contact between a pair of users. Here, we set the duration of each contact to 10s.

In addition, it is noticed that users in the two real tracing datasets have various movement and contact patterns, and they join and leave the conference sites with different schedules. If we continued to periodically activate each user's data dissemination task for energy-saving purpose, users would have

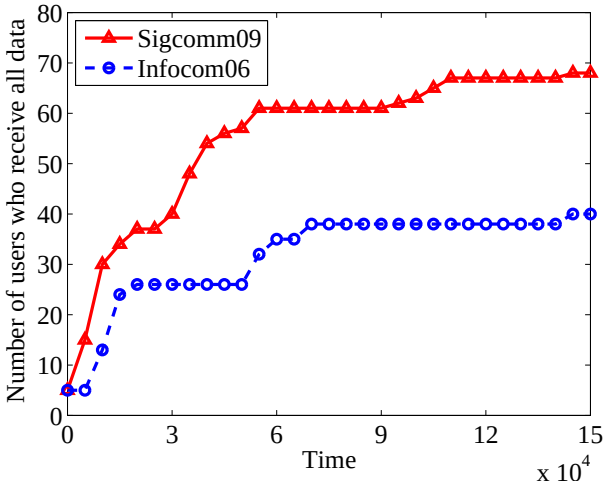


Fig. 6.13: Number of users who receive all the data.

very few opportunities to disseminate data. Therefore, we choose to suspend periodic activation for the real tracing datasets; that is, users are active all the time in Phase II. In the simulation, we set the number of seeds to 5, the number of messages to 10, and g to 5 for the two datasets, respectively.

Fig. 6.13 shows the number of users who have received all messages with the increase of time for the two datasets. As seen in Fig. 6.13, our mechanisms also work well in the real scenarios. For the two datasets, as time goes on, a fairly large proportion of users receive all messages. Here, we extend the duration of data dissemination by a large margin compared to previous simulations, because in real scenarios users have various movement patterns and schedules so that they do not encounter each other so frequently as in the previous ideal scenarios. Therefore, the duration of data dissemination needs to be set long enough for users to encounter and perform data transmission.

In Fig. 6.13, we can see that after the intervening and matching of the BS, the number of users who have received all messages has improved substantially. On the other hand, it is worth noting that the data dissemination with the trace `Sigcomm09` proceeds more successfully than that with the trace `Infocom06`. This is because the social relationships in `Sigcomm09` are more dense; that is, each user generally has more friends in this trace. As a consequence, users will have more potential target receivers in Phase II and there will be more pairs of socially connected users in Phase III, so that more users can benefit in these phases.

6.4 Summary

In this chapter, we propose a three-phase approach for data dissemination in MSNs via D2D communications, which explores social-awareness and opportunistic contacts with user mobility, and takes into account users' behavior characteristics and incentives. Our approach includes Phase I for initial seed selection and message dispatching to seeds, and Phase II and Phase III for data forwarding among socially connected users and among cooperative users, respectively. Phase I exploits users' social relationships in the social network and physical contacts with mobility in the physical network to improve data dissemination efficiency. The two phases of data forwarding consider both users' altruistic and selfish behaviors, and properly address the corresponding social incentive and cooperative incentive. The proposed

mechanisms for message selection and cooperation pairing accommodate the incentive constraints of users without resorting to monetary rewards. Thus, the mechanisms are free of the hassle of payment transfer. The theoretical analysis for the message selection mechanism proves its truthfulness. Extensive simulation results further demonstrate the effectiveness of the three-phase approach with various synthetic and real tracing datasets. The performance of our proposed mechanisms is fairly close to that of the optimal algorithms.

Chapter 7

Conclusions and Future Work

7.1 Conclusions

Data dissemination finds a wide range of applications in people's daily life and it has become an appealing mobile application with the increasing penetration of smart devices and deployment of ubiquitous wireless networks. The promising D2D communication techniques and the valuable information of people's social relationships provide effective means to facilitate data dissemination in wireless networks. In this thesis, we aim to design social-aware schemes to enable efficient data dissemination via D2D communications in wireless networks. In order to perform data dissemination effectively, we need to tackle several critical issues: (1) how to properly select initial seeds and coordinate the subsequent data transmission among users based on the corresponding application requirements of data dissemination; (2) how to

efficiently mitigate the interference of D2D communication to enable more transmission links in the network; and (3) how to carry out efficient data dissemination given users' social incentive constraints and how to design incentive mechanisms to encourage users to contribute to data dissemination. In order to solve the above challenges, we propose several data dissemination schemes, which are summarized and highlighted in the following.

Firstly, we propose a centralized spanning tree based data dissemination scheme to reduce energy consumption and transmission finishing time of data dissemination. We model the potential D2D communication links among users with social relationships as a bidirectional graph. Then we use graph theory to perform a series of structure transformations to find a proper minimum spanning tree, based on which we can choose the initial seeds and transmission paths. In addition, a transmission schedule algorithm is proposed to determine the transmission order for nodes on the paths, which utilizes the effect of parallel transmission. In the simulations, we compare our algorithms with a random approach and a coalition graph game approach using different network sizes, numbers of seeds, and social connection structures. The simulation results show that our proposed approach can effectively balance between energy consumption and transmission finishing time, and improve the two aspects in different scenarios.

Secondly, we propose a distributed coalitional graph game based data dissemination scheme to improve energy efficiency of data dissemination given users' social incentive and power budget constraints. A coalitional graph

game is designed to iteratively derive a proper transmission graph satisfying the constraints, i.e., a spanning tree, to coordinate the transmission of the BS and users in the network. In our coalitional graph game, we extend the definition of a feasible strategy to avoid the problem of obtaining an invalid transmission path, i.e., a cycle without a transmission source. In the simulations, we first show the convergence performance of the proposed approach. Then we compare our approach with the optimal solution, a reference coalitional graph game approach and a heuristic approach with different network scales and social network structures. Simulation results show that the power consumption of our proposed approach is fairly close to that of the optimal solution in small-scale D2D networks and outperforms that of two reference schemes in various scenarios. Finally, the impact of power budget constraint on the performance of data dissemination is investigated.

Thirdly, we propose a preference-aware social community based data dissemination scheme to satisfy target users' preferences for messages. Our scheme takes advantage of the strength of a user's direct and indirect social connections with the members in its social community for data dissemination. Our approach first selects the initial sources with maximum coverage potentials, which is obtained by solving a weighted maximum coverage problem. Then, the subsequent data forwarding between sources and remaining users is performed by utilizing a monetary auction-based incentive mechanism and a moneyless matching-based incentive mechanism, depending on the application environment. The monetary mechanism obtains the global

optimal solution and achieves truthfulness, but it involves transfer of monetary rewards. In contrast, the moneyless mechanism enables a lightweight implementation and guarantees two-sided stability. To evaluate the performance of the proposed approaches, we develop novel schemes to generate and preprocess synthetic and real tracing dataset. Extensive simulation results with these datasets demonstrate the high efficiency of our approaches in terms of total utility and completion ratio.

Fourthly, we propose a three-phase approach for data dissemination in MSNs, which further exploits users' opportunistic contacts with mobility. In Phase I, initial seeds are chosen based on a social-physical graph, which fuses social network and physical network. In Phase II and Phase III, subsequent data forwarding are performed by accommodating users' altruistic and selfish incentive constraints, respectively. Mechanisms for message selection and cooperative pairing are proposed for these two phases respectively. We theoretically prove that the proposed message selection mechanism for Phase II is truthful. Extensive simulations are carried out to evaluate the performance of our proposed approach using both synthetic and real tracing datasets. The simulation results show that the performance of our proposed approach in terms of total utility and average completion ratio fairly approaches that of the optimal approaches and outperforms that of a reference approach.

7.2 Future Work

There are several potential future research directions that our research can be further extended.

Firstly, some other economic theory model can be utilized to design incentive mechanisms for data dissemination. In addition to the coalitional graph game that we have used in this thesis, coalition formation game [54], which is another important tool in cooperative game theory, can also be applied in the design of incentive mechanisms for data dissemination. Coalition formation game can be designed to enable the formation of collaborative groups in the network, where users within the same group help each other by mutually transmitting the messages that others need. The formation of collaborative groups and interactions within a group can be determined from users' individual perspectives, i.e., whether their own utilities are maximized by joining a group. This will be different from the system goal of maximizing the global graph utility in coalitional graph game, which can better satisfy users' individual incentives.

Besides, Nash bargaining theory [87], another popular area of cooperative game theory, is also a promising tool for the design of incentive mechanisms. One-to-many bargaining model can be used to model the information interaction and bargaining process between the BS and multiple nodes in the network, so as to determine the seeds to receive data from the BS and the data transmission between seeds and remaining nodes in the network.

Secondly, the D2D data dissemination model considered in this thesis can be further integrated with the data dissemination framework in which a mobile BS is used. In opportunistic environments, due to the intermittent contacts among nodes in the network and transmission range limitation of D2D communication techniques, it is relatively difficult to satisfy a large proportion of the target users in a timely manner. In this circumstance, it is more effective to deploy a mobile BS, which moves around to broadcast data to users in the network. In [42], a geocommunity-based broadcasting scheme utilizing a mobile BS is proposed for data dissemination in MSNs. Nonetheless, only one-hop data broadcasting from the mobile BS to regular users is considered in [42], while the data sharing and delivery among users is ignored. The mobile BS usually needs to travel a long distance and stay in some locations for a long time to disseminate data to more users in the network. Thereby, our data dissemination model can be further combined with this framework to facilitate data dissemination. The mobile BS can broadcast the messages to available users in certain regions and then let these users further distribute data to others via opportunistic contacts using D2D communications. The movement trajectory design for the mobile BS is a challenging issue, which needs to consider the spatial distribution and transmission capabilities of D2D users.

Thirdly, a novel social network can be utilized to promote users' interactions in data dissemination. In this thesis, we consider users' social incentive constraint, i.e., a user prefers to transmit data to other people who are socially

connected with. In this way, data transmission is mainly restricted to the people that have already known each other. Recently, augment reality technique is applied in [88] to construct a new kind of distributed social network, which enables new people in the vicinity to initiate conversations and exchange information instantly to enhance social interactions. This distributed social network can be adopted in our data dissemination model, by which the potential transmission links among people that are previously strangers are further utilized. Corresponding information protocols should be extended to make full use of these transmission links to promote data dissemination.

Fourthly, we can extend our research work for data dissemination in the context of internet of things (IoT). Currently, the number of devices connected to IoT is increasing at a tremendous speed. A challenging issue is how to efficiently disseminate data to a massive number of devices in IoT. Meanwhile, the architecture of IoT is experiencing evolution, among which social relationships between owner of devices and node mobility are important factors to be considered [89]. Our research work provides promising solutions to data dissemination in IoT, where further extensions and adaptations may be needed to accommodate the characteristics and requirements of IoT.

Fifthly, our research work for data dissemination can be further extended by exploring privacy and security issues. In this thesis, we generally assume that users in the network are benign and cooperative. Nonetheless, in the real life, there may exist some malicious nodes that are interested in snooping other users' privacy or launch some active attacks to benefit themselves in data

dissemination [90]. Thereby, data dissemination solutions are necessary to preserve users' privacy such as identity and location, and resist different attacks to promote users' willingness for participating in data dissemination. It is promising that our research work is further integrated with anonymization techniques and encryption techniques.

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