SHARE COMMUNICATION AND COMPUTATION RESOURCES ON MOBILE DEVICES: A SOCIAL AWARENESS PERSPECTIVE

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[1] It costs US$10 for every 1 GB data usage exceeding the budget, according to one of China's largest telcos, Unicom.

[2] The battery capacities of different mobile devices range from 1000 mAh to 5000 mAh, while data plans range from 0.5 GB per month to 10 GB per month.

[3] The motivation for offloading computation tasks can also be the lack of computation capability, which is not the focus of this article.

ABSTRACT

The increasing demand of mobile applications creates challenges for mobile devices on energy consumption and data usage. As a solution, device-to-device communication can serve as a powerful paradigm in future cellular networks to enable local cooperation of mobile devices. By leveraging social awareness, users can share surplus communication and computation resources on their mobile devices to stimulate beneficial cooperation, which can cut down on energy consumption and data usage. In this article, we propose a joint task-data offloading framework for mobile devices that have insufficient energy budgets or data usage budgets. Based on the proposed framework, a mobile device association problem is formulated and solved by exploiting matching-based and game-theory-based schemes. Extensive numerical results show the effectiveness of the schemes for the proposed framework in the reduction of energy consumption and data usage.

INTRODUCTION

Social and multimedia-type mobile applications, which are favored by a majority of mobile users, are demanding in both network bandwidth and computation capability. Such bandwidth and computation demanding mobile applications pose a significant challenge for mobile devices. Clearly, today's mobile devices (e.g., smartphones) are facing two challenges:

- Limited energy budget (energy thirst). When continuously running computation-demanding applications (e.g., video transcoding and 3D gaming) on a mobile device, the energy budget is used up soon.
- Limited budget for monthly data usage. Data-intensive applications like high-definition video streaming can exhaust a cellular user's data usage budget easily, and the fees for exceeding the data usage budget are quite expensive.[1] In addition, heterogenous energy and data usage budgets across different mobile devices are commonly observed;[2] can mobile devices with lower energy or data usage budgets run social and multimedia-type applications without draining batteries or causing extensive data usage fees?

The emerging device-to-device (D2D) communications can be a promising paradigm that enables direct communication between two mobile devices in proximity by reusing the cellular spectrum without traversing the base station (BS) and the core network [1]. Recently, D2D communications in cellular networks have drawn much attention from both industry and academia.

User cooperation via D2D communications is viewed as a solution to the unbalanced energy and data usage budgets [1, 2]. Regarding the energy budget, a device with sufficient remaining energy can serve as a surrogate and help a device with low remaining battery power to execute computation-demanding tasks,[3] and is called a mobile cloudlet [3]. Regarding the data usage budget, a device with sufficient remaining data usage budget can relay information from other devices to a BS [4], considering that D2D communication does not consume data usage budget. However, how to motivate users of mobile devices to help others is critical. Since the sharing of resources typically incurs overhead such as energy consumption and data usage, a user of a mobile device may not be willing to help others for free without proper incentive. From a social awareness perspective, the underlying rationale for considering social ties is that the mobile devices are carried by human beings, and knowledge of human social ties can be utilized to add more opportunities for resource sharing [5–7]. Generally, there are two important types of social ties. The first type is *social trust*, which is mutual trust observed among family members, friends, and colleagues. A user is willing to help another user (or vice versa) without any immediate reward when they have trust. Unfortunately, the social trust between two cellular users in proximity usually exists in limited locations like a residence or an office. A second type is *social reciprocity*, which is a powerful mechanism for

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promoting mutual beneficial cooperation among unfamiliar users without any trust; that is, multiple users can cooperate to be better off. However, social reciprocity is not easy to achieve when only one type of resource is considered. For example, a user with a sufficient communication (computation) resource will not join a socially reciprocal group because she/he does not need additional communication (computation) resources.

A possible solution is that mobile devices can form socially reciprocal groups and achieve a win-win situation through exchanging different types of resources (e.g., communication and computation resources). For example, device A has sufficient data usage but is running on low battery power. When device A plans to transcode a captured video clip, it can offload such a task to nearby device B, which has sufficient energy budget and computation capability but with insufficient data usage budget. The proposed framework is referred to as **joint task-data offloading** in this article. Specifically, there are two key challenges to realize the proposed framework:

- A proper system model design for joint task-data offloading
- Effective mobile device association mechanisms that form socially reciprocal groups of cooperation

The main contribution of this article is to solve the above challenges.

The related works fall into two categories: share communication resources (cooperative networking) and share computation resources (task offloading) via D2D communications. On one hand, there are a plethora of studies about D2D-based relaying. Cao *et al.* [8] proposed a cooperative video multicast system and showed that by allocating dedicated cellular spectrum to D2D communications, the user's perception of video quality can be greatly enhanced. For heterogeneous cellular networks, a D2D-based load-balancing framework was proposed in [9], which can flexibly offload traffic among different tier cells and achieve efficient load balancing according to their real-time traffic distributions. In [1], the authors considered a scenario involving collocated cellular networks and D2D networks, in which the cellular network leverages D2D users as cooperative relays and decides the optimal spectrum-sharing mode for D2D communications. On the other hand, more and more studies are about mobile task offloading. Li *et al.* [3] analyzed boundaries of the computing capacity and computing speed of a cloudlet, in which resource-constrained mobile devices can offload tasks to resource-rich mobile devices. In [10], Jiang *et al.* proposed a Lyapunov optimization-based scheme for offloading tasks to multi-core mobile devices. In [11], the authors established a distributed computing framework based on mobile devices and put forth a scheduling algorithm to minimize the makespan (completion time) of a set of computing tasks. To the best of our knowledge, this is the first time that a joint task-data offloading framework, which can significantly reduce the energy consumption and data usage for mobile devices, has been proposed.

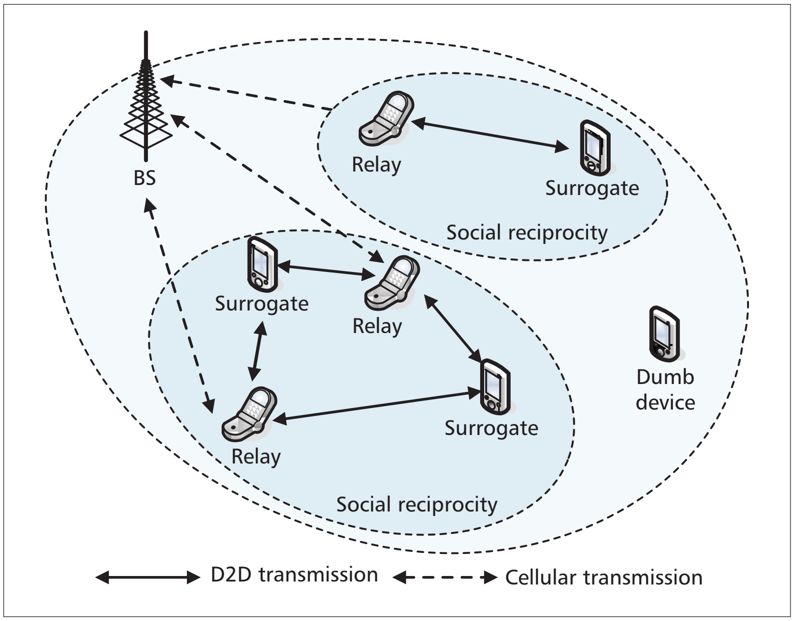

Figure 1. An illustration of the cellular network with socially-aware D2D resource sharing.

This article is organized as follows. In the next section, we introduce the system model of D2D communications-based resource sharing. Then the joint task-data offloading framework and two mobile device association schemes are presented. Numerical results show the performance comparison of the proposed schemes with the baseline scheme in the following section. Conclusions are drawn in the final section.

Resource Sharing Based on Device-to-Device Communications

In this article, we consider an orthogonal frequency-division multiple access (OFDMA)-based cellular network, which can be Long Term Evolution (LTE)-Advanced [4]. As shown in Fig. 1, a cell in the cellular network is centered around a BS that operates over a licensed spectrum band, and there are a number of mobile devices. Through OFDMA modulation, the spectrum band can be divided into a number of orthogonal sub-channels with equal bandwidth, and the time is equally divided into OFDMA frames, each of which lasts several milliseconds. The BS supports operator-controlled D2D communications, which means, besides a cellular link between a mobile device and the BS, two mobile devices can communicate directly with each other over a D2D link. Notice that a D2D link remains controlled by the BS. Specifically, the BS is in charge of the peer discovery, link establishment/maintenance, and spectrum allocation for D2D communications. During an OFDMA frame, each mobile device that has communication demand can be allocate at most a sub-channel for data transmission; the D2D link is allowed to share the sub-channel of a cellular link with constrained transmit power to protect the cellular link from severe interference [1].

As illustrated in Fig. 1, we define three types of mobile devices: surrogate, relay, and dumb devices.

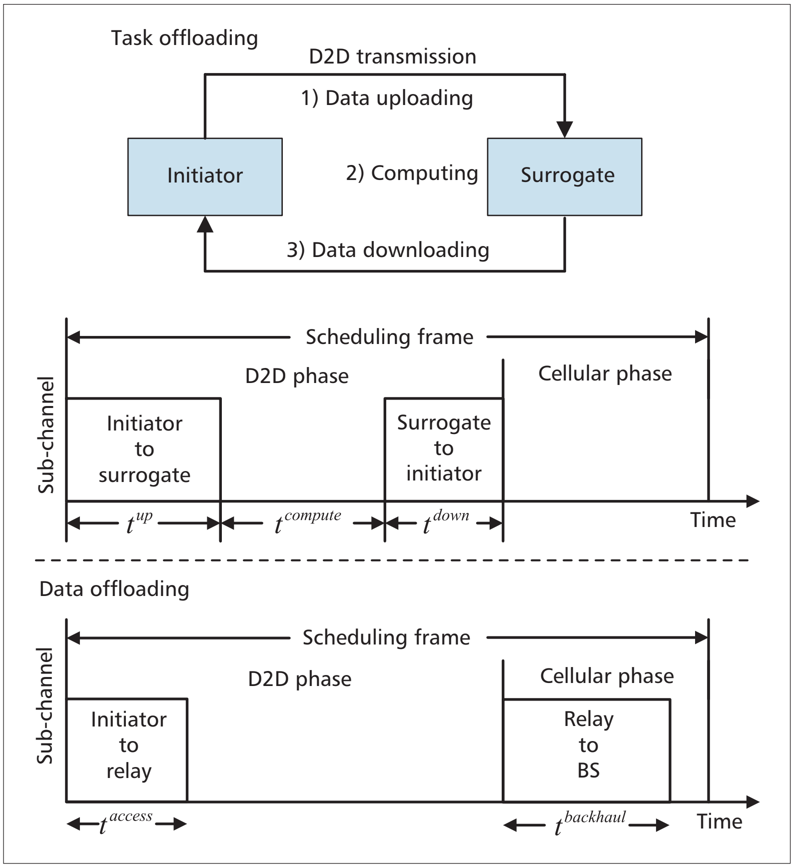

Figure 2. Illustrations of task offloading and data offloading models.

- **Surrogate**: This is a mobile device with sufficient energy budget (i.e., the remaining battery power is beyond the threshold set by the user) and computation capability, which has the potential to provide task offloading services to other mobile devices.
- **Relay**: This is a mobile device with sufficient data usage budget (i.e., the remaining data usage budget is beyond the threshold set by the user), which has the potential to provide data offloading services to other mobile devices.
- **Dumb device**: This is a mobile device that does not have the potential to provide task offloading services or data offloading services.

Since we consider the scenario that mobile devices share communication and computation resources among each other to achieve a win-win situation, it is reasonable to assume that a surrogate expects to reduce its data usage by providing task offloading services, and a relay expects to reduce its energy consumption by providing data offloading services. In this article, we do not take into account the case that a surrogate/relay would help dumb devices without any immediate reward because it breaks the principle of social reciprocity. Similarly, we consider a mobile device with sufficient energy and data usage budgets as a dumb device because it does not have the motivation to exploit social reciprocity. In summary, both surrogate and relay are willing to share one type of resource in order to obtain another type of resource.

Compared to the timescale of an OFDMA frame (several milliseconds), the timescale of the task offloading and data offloading processes can be much larger (from hundreds of milliseconds to several seconds). To properly schedule the communication and computation resource sharing among mobile devices, we define a **scheduling frame** with length T (in seconds) as a larger timescale frame for the scheduling of task/data offloading processes. Further, we assume that a sub-channel would be assigned to a relay during the scheduling frame if this relay is in a socially reciprocal group, while sub-channels would not be assigned to surrogates in socially reciprocal groups during the scheduling frame. Moreover, a scheduling frame is divided into two parts, a D2D phase and a cellular phase.[4]

In what follows, the models for task offloading and data offloading are presented.

Task Offloading Model

With the purpose of cutting down on a mobile device's energy consumption, we consider the computation of resource-demanding mobile tasks (e.g., video transcoding) that are suitable for being offloaded to a surrogate. For a surrogate, the computation capability allocated to a mobile task is limited, and thus the computing time is not negligible.

At the beginning of a scheduling frame, each initiator (the mobile device that requires task offloading) should broadcast a mobile task offloading request over the control channel, and each task offloading request contains a *task metadata*, which is the information of task offloading requirements. When the initiator has been associated with a surrogate, the task offloading process begins. Specifically, the task offloading process of an initiator, which consists of three sequential stages [12], is illustrated in the top part of Fig. 2.

- **Data uploading**: The initiator uploads D^{up} bytes of task data (e.g., encoded frames from a specific formatted video) to the surrogate via D2D transmission over the allocated sub-channel in the D2D phase. The data uploading is completed when the data transmission from the initiator to the surrogate is finished. The duration of this stage is denoted by t^{up}.
- **Computing**: The uploaded task (transcoding of video frames) is computed by the surrogate; then the output data is ready to be sent to the initiator. The duration of this stage is denoted by $t^{compute}$, which is affected by the task load and the computation capability of the surrogate.
- **Data downloading**: When the computing stage ends, the surrogate sends D^{down} bytes of output data (e.g., encoded frames with the target format) to the initiator via the D2D transmission over the allocated sub-channel in the D2D phase. The data downloading is completed when the output data transmission is finished. The duration of this stage is denoted by t^{down}.

Obviously, the execution time of an offloaded mobile task is the makespan of all the above three stages and the intervals between two successive stages. Since we study the problem in a low-mobility scenario (speed ≤ 1.5 m/s), it is assumed that the distance between the initiator and the surrogate would not change much during

[4] It is possible that the sub-channel assigned to a relay during the D2D phase in a scheduling frame is reused by other links in order to tighten the spectrum reuse factor in this cell.

the mobile task offloading process (could range from hundreds of milliseconds to a few seconds). Moreover, the deadline of the task offloading is assumed to be at the end of the scheduling frame, and the end of the data downloading stage should not go past this deadline.

Notice that the task offloading may not always save energy. As shown in [2], task offloading with a large amount of data to be transferred could result in waste of energy on communication, which offsets the energy saving by offloading computation. In this article, we only consider the case in which the task offloading is energy saving.

Data Offloading Model

At the beginning of the scheduling frame, the mobile device is termed as an initiator of data offloading when it broadcasts a data offloading request over the control channel, to offload the data transmission to another mobile device (relay). Generally, cooperative relaying is an extension of distributed, multiple-input multiple-output communications [4], which can be fulfilled by D2D transmission. Specifically, the relaying communication consists of two links, the access link between the initiator and the relay, and the backhaul link between the relay and the BS.

As illustrated in the bottom part of Fig. 2, the relay can help the initiator when the latter has insufficient data usage budget. During the D2D phase, the initiator transmits its D bytes of data to the selected relay (access link), and the data transmission lasts t^{access}. During the cellular phase, the relay forwards the received D bytes of data to the BS via the decode-and-forward method (backhaul link), and the data transmission lasts $t^{backhaul}$. Obviously, the minimum requirement of a successful data offloading is that t^{access} is no longer than the D2D phase and $t^{backhaul}$ is no longer than the cellular phase of a scheduling frame.

Joint Task-Data Offloading Framework

One salient feature of the proposed joint task-data offloading framework is to stimulate socially reciprocal cooperation among mobile devices. Therefore, a win-win situation can be achieved through exchanging communication and computation resources. The case in which a relay and a surrogate form a socially reciprocal group is illustrated in Fig. 3. During the D2D phase, the relay first sends its task data to the surrogate, as in the data uploading stage of the task offloading. The following computing stage can be utilized to transmit data from the surrogate to the relay through the access link of data offloading. After that, the surrogate returns the resulting data to the relay, as in the data downloading stage of the task offloading. During the cellular phase, the data from the surrogate is retransmitted to the BS by the relay through the backhaul link of data offloading.

Obviously, it is crucial to study the principle of forming socially reciprocal groups among surrogates and relays. A surrogate (relay) prefers to help a relay (surrogate) at minimum cost when its own data (task) offloading request has been satisfied. Specifically, denote $cost^{task}(i, j)$ as the cost of surrogate i that helps relay j offload its computation task, and $cost^{task}(i, j)$ can be calculated based on the summation of $t^{up}(i, j)$, $t^{compute}(i, j)$, and $t^{down}(i, j)$. Meanwhile, denote $cost^{data}(i, j)$ as the cost of relay j that helps surrogate i to offload its data transmission to the BS, and the calculation of $cost^{data}(i, j)$ can be related to $t^{access}(i, j)$ because a larger $t^{access}(i, j)$ would reduce the sub-channel time for the data transmission of the task offloading. It is not difficult to find that the values of $t^{up}(i, j)$, $t^{down}(i, j)$, and $t^{access}(i, j)$ depend on D^{up}, D^{down}, D and the D2D transmission rate between surrogate i and relay j, and the value of $t^{compute}(i, j)$ depends on the load of the task from relay j and the computation capability of surrogate i.

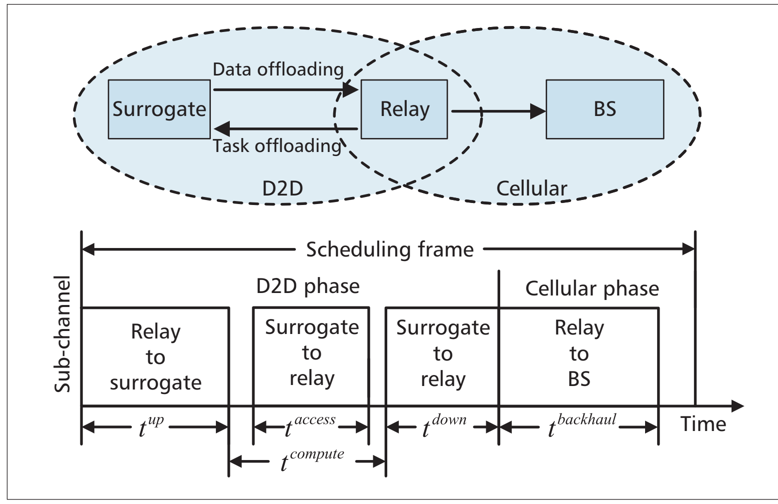

Figure 3. An illustration of the joint task-data offloading based on D2D communications.

The mobile device association problem can be solved by two mobile device association schemes to form surrogates and relays into socially reciprocal groups, from two different perspectives:

- **From a system operator's perspective**, the objective of the mobile device association problem is to minimize the overall cost of all mobile devices. We propose a centralized matching-based scheme deployed at the BS to obtain the mobile device association plan.
- **From a mobile device user's perspective**, the objective of the mobile device association problem is to minimize its own cost when joining a socially reciprocal group. We propose a game-theory-based scheme deployed at each mobile device to obtain the mobile device association plan in a distributed manner.

In the following part of this section, details about the above two schemes are given.

Matching-Based Scheme

One centralized solution to the mobile association problem is to match one surrogate to one relay and let those two become a socially reciprocal group. As a result, the original problem can be transformed into a weighted bipartite matching problem.

Here we use an example to show the problem solving process. As shown in Fig. 4, there are two surrogates (surrogate 1 and surrogate 2) that need the data offloading service, and there are

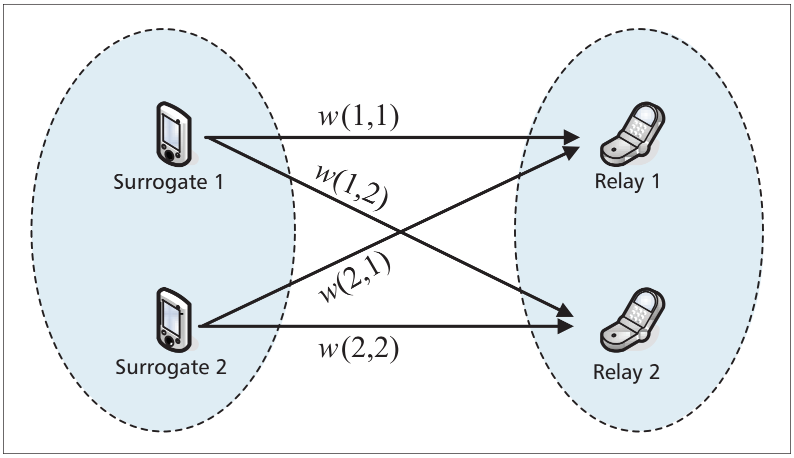

Figure 4. An illustration of the weighted bipartite matching for mobile device association.

two relays (relay 1 and relay 2) that have been allocated two sub-channels and need the task offloading service. Next, denote weight $w(i, j) = \alpha_1\, cost^{task}(i, j) + \alpha_2\, cost^{data}(i, j)$, where α_1 and α_2 are positive, and $\alpha_1 + \alpha_2 = 1$. Then a weighted bipartite graph (Fig. 4) can be constructed with weights $w(1, 1)$, $w(1, 2)$, $w(2, 1)$ and $w(2, 2)$. By using the Hungarian algorithm, the matching plan (surrogate-relay pairs) with a minimum sum of weights (overall cost) can be determined. The time complexity of constructing the bipartite graph is $O(N^2)$, and the weighted bipartite matching problem can be optimally solved by use of the Hungarian algorithm with a time complexity of $O(N^3)$ [13].

Game-Theory-Based Scheme

In order to develop a distributed mobile device association scheme with lower complexity, we now formulate the mobile device association problem for the joint task-data offloading framework as a coalition game [14].

First, consider the critical part of the coalition game formulation, that is, constructing the preference order list for each mobile device *i*. A preference order list is a set of IDs of mobile devices that mobile device *i* is able to help (complete task offloading or data offloading before the end of the scheduling frame). IDs in a preference order list are in descending order according to the preference. Intuitively, the preference of a mobile device is determined according to its type:

- Surrogate *i* prefers to help relay *j* with as low as possible $cost^{task}(i, j)$.
- Relay *j* prefers to help surrogate *i* with as low as possible $cost^{data}(i, j)$.

Accordingly, we can construct a preference order list for each mobile device. To support self-cycle reciprocal groups, add mobile device *i* to the end of its own preference order list.

Based on the preference order list introduced above, we next formulate a coalition game Omega with key elements listed as follows:

- **Set of Players**: the set of surrogate-type and relay-type mobile devices.
- **Set of Cooperation Strategies**: the set of all possible takers (mobile devices helped by others) associated with all mobile devices (one-to-one mapping).
- **Characteristic of Coalition**: the mapping from coalitions to cooperative strategies. Specifically, for coalition Δ (a non-empty subset of the set of players), each mobile device in Δ helps one mobile device while helped by one mobile device.[5] Meanwhile, each mobile device not in Δ would not participate in any cooperation.
- **Preference of Player**: mobile device *i* prefers a cooperation strategy A to another cooperation strategy B if and only if *i*'s taker in strategy A is preferred by mobile device *i* rather than that in strategy B, according to the preference order list.

The core of this coalitional game is a set of *stable* cooperation strategies, for which there does not exist new coalition Δ' and its characteristic cooperation strategy such that mobile devices in coalition Δ can deviate and associate with a better taker by cooperation in coalition Δ'. The objective of the game-theory-based scheme is to find a core solution (i.e., one cooperation strategy in the core). Given the preference order lists of all mobile devices, a preference graph can be constructed for a given set of mobile devices. Specifically, the given set of mobile devices is the set of vertices, and the set of edges represents the preferences. There is an edge directed from mobile device *i* to mobile device *j* if and only if mobile device *j* is the most preferred taker (MPT) among the set of mobile devices according to the preference order list of mobile device *i*.

According to [8], we propose a distributed, socially reciprocal group formation algorithm. The basic operation of the algorithm is to find reciprocal cycles through local probing messages from mobile devices. For example, mobile device *i* first sends a probing message to its MPT, mobile device *j*. Mobile device *j* then forwards this message to its MPT. Such a process continues until mobile device *i* receives this message from another mobile device if a reciprocal cycle exists. The proposed algorithm's detailed steps are given as follows:

- **Step 1**: During the random access window, each mobile device with indicator 1 (i.e., this mobile device is not involved in any reciprocal cycle) competes for the opportunity to perform reciprocal cycle discovery.
- **Step 2**: When mobile device *i* wins the competition, it first broadcasts an Occupy message to declare that it will perform reciprocal cycle discovery soon, and other mobile devices do not perform reciprocal cycle discovery until mobile device *i* finishes. Then mobile device *i* transmits a Probe message to its MPT, mobile device *j*.
- **Step 3**: Mobile device *j*, which receives the Probe message, will check its indicator's value. In particular, if the indicator equals 0 (i.e., mobile device *j* has been involved in some reciprocal cycle), mobile device *j* sends a Skip message to mobile device *i*, and then mobile device *i* sends the Probe message to the next most preferable taker according to the preference order list. If the indicator equals 1 (i.e., mobile device *j* has not been involved in any reciprocal cycle), mobile device *j* attaches its ID to the Probe message. Next, it transmits the Probe message to its MPT.

[5] For a coalition with more than one player, each mobile device helps one other mobile device, and is helped by one other mobile device; for a coalition with a single player, the mobile device is actually not involved in any cooperation.

- **Step 4**: The process continues until there is a mobile device k that has received the Probe message before (i.e., a reciprocal cycle is identified). Mobile device k sets its indicator to 0; then it can obtain the list of mobile devices from the cycle (because of Step 3). Next, mobile device k broadcasts a feedback message including the IDs of mobile devices that form the reciprocal cycle to all the mobile devices in the system. Mobile device k is also the leader of the cycle.
- **Step 5**: Each mobile device with indicator 1 repeats Steps 1 to Step 4 until a new reciprocal cycle is discovered. Such a reciprocal cycle discovery process ends when all the mobile devices' indicators equal 0.

It is not difficult to prove that the time complexity of the game-theory-based mobile device association scheme is $\mathcal{O}(N^2)$.

Numerical Results

In this section, numerical results are presented through computer-based simulations. Regarding the simulation scenario, a cluster of mobile devices is scatted in a round area and the area's radius is 100 m, which ensures that all the mobile devices in the cluster can directly communicate with each other through D2D communications. The distance between the BS and the cluster center is 500 m. There are N active mobile devices, which are divided into two types, surrogate and relay. It is assumed that 50 percent of mobile devices are surrogates. Each mobile device's transmit power[6] equals 100 mW, and the noise power density is set to –174 dBm/Hz. Each relay has been preassigned a sub-channel with a bandwidth of 1 MHz, while each surrogate does not have a preassigned sub-channel. Additionally, the path loss of a cellular link and a D2D link are calculated according to the COST-231 Type E model (Walfish-Ikegami) and Type F model (WINNER II B1) [15], respectively. Large-scale shadowing and small-scale fading are also considered in the channel model. We denote T (in seconds) as the length of the scheduling frame, which is divided into two parts, the D2D phase and the cellular phase, and the percent of the cellular phase is 0.2.

Moreover, the computation capability of a surrogate ranges from 61.5 to 76.8 units/s, the computation capability of a relay ranges from 20.5 to 25.6 units/s, the computation task load ranges from 15.3 to 19.2 units, the data offloading load ranges from 46 kB to 57.5 kB, the uploaded data of task offloading ranges from 38.3 kB to 47.9 kB, and the downloaded data of task offloading ranges from 30.6 kB to 38.3 kB. The energy consumption of communication is calculated according to the transmit power of the mobile device (i.e., 100 mJ/s). According to experiments on an Android smartphone (XiaoMi Note2) with 2.0 GHz 8-core CPU and 3060 mAh battery capacity, we set the energy consumption of running resource-demanding tasks as 800 mJ/s.

In the simulation, we consider three different schemes as follows:

- **No Cooperation**: This is the case in which no cooperation is enabled among surrogates and relays. This means that a mobile device with an insufficient data usage budget has to transmit its data to the BS by itself, and a mobile device with an insufficient energy budget has to execute the computation resource-demanding task locally.
- **Matching**: This is the matching-based mobile device association scheme for the proposed framework, which is centralized.
- **Game**: This is the game theory-based mobile device association scheme for the proposed framework, which is distributed and has lower complexity.

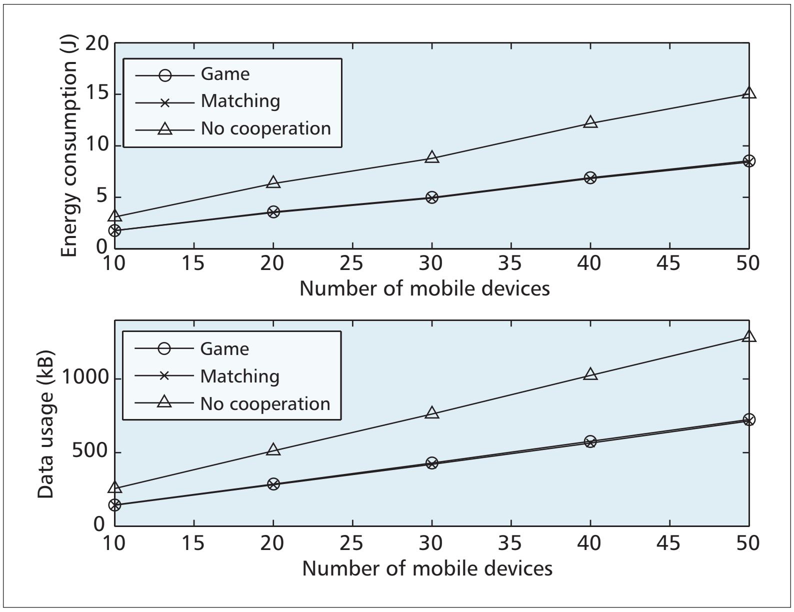

Figure 5. Energy consumption and data usage using three schemes vs. the number of mobile devices.

We consider two performance metrics, energy consumption (the total energy consumed by relays) and data usage (the total data usage of surrogates that directly transmit data to the BS). Notice that when executing a task locally, the energy consumption of a relay is on computation; when offloading a task to a surrogate, the energy consumption of a relay is on communication for task data uploading and relaying transmission. In what follows, we vary the number of mobile devices and T to compare the performance of different schemes for a variety of scenarios.

The curves of energy consumption (in Joules) and data usage (in kilobytes) using three schemes vs. the number of mobile devices are depicted in Fig. 5. We could find that both game-theory-based and matching-based schemes can cut down on energy consumption and data usage, since they can stimulate relays and surrogates to form socially reciprocal groups, which can significantly decrease energy consumption and data usage. Compared to the no cooperation scheme, the game-theory-based scheme can reduce 44 percent of energy consumption and 45 percent of data usage when the number of mobile devices is 20, and the matching-based scheme reduces slightly more energy consumption and data usage than the game-theory-based scheme at the cost of higher complexity and the requirement of a centralized controller.

In Fig. 6, the curves of energy consumption and data usage by using three schemes vs. the scheduling frame length T are depicted when N

[6] Dynamic power control is not the focus of this article.

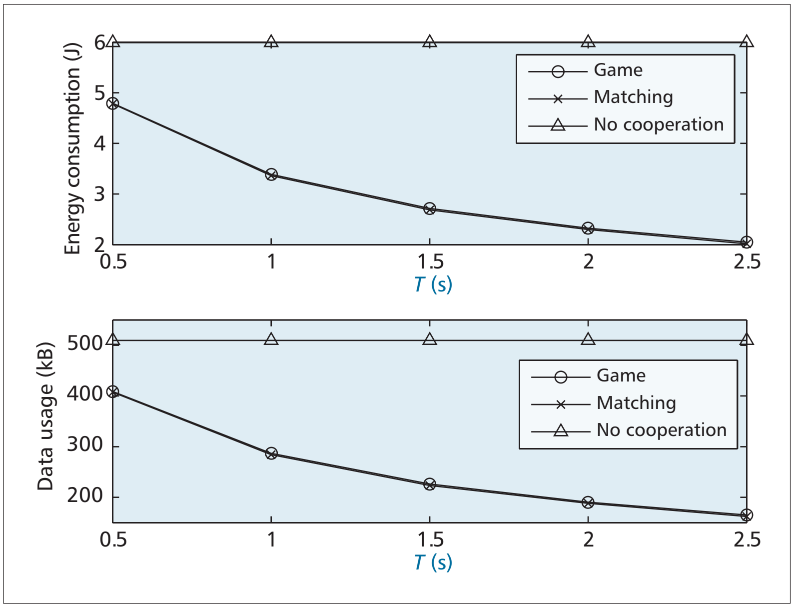

Figure 6. Energy consumption and data usage using three schemes vs. the scheduling frame length T.

is fixed to 20. Obviously, schemes for the proposed framework can reduce more energy and data usage consumption with the increase of T.

In summary, the two schemes for the proposed framework can efficiently reduce the energy consumption and data usage for mobile devices compared to the baseline scheme without cooperation among mobile devices.

Conclusion and Future Direction

In this article, a socially aware joint task-data offloading framework based on D2D communications has been proposed. Specifically, a mobile device association problem was formulated to socially organize mobile devices that have insufficient energy budget or data usage budget into socially reciprocal groups. Both centralized and distributed schemes were developed to achieve the reduction of energy consumption and data usage. Through numerical results, schemes for the proposed framework can significantly reduce the consumption of energy and data usage, which improves the user experience. Possible future directions could be:

- Considering more practical cases, for example, one surrogate serves multiple relays and one relay serves multiple surrogates
- Considering joint transmit power control and sub-channel allocation for the proposed joint task-data offloading framework
- Analyzing the performance bound of the proposed joint task-data offloading framework

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