Rally: Device-to-Device Content Sharing in LTE Networks as a Game

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***Abstract*—Even with modern physical-layer technologies in LTE networks, the capacity of cellular networks is still far from sufficient to satisfy the insatiable bandwidth demand of mobile applications. Owing to common interests among mobile users, Device-to-Device (D2D) communication has emerged as a viable alternative to offload cellular traffic, with the promise of substantially alleviating the need for cellular network bandwidth. In this paper, we first carry out an extensive theoretical analysis based on a game theoretic approach, and show that the objective of maximized cellular offloading is equivalent to maximizing the social welfare in a trading network, where the content to be shared is the commodity, and mobile users are buyers or sellers. We next design *Rally*, a set of distributed strategies that can converge to a subgame perfect Nash equilibrium in the content sharing game. Both our theoretical analyses and simulation results have shown the effectiveness of *Rally*, in that it can indeed maximize cellular traffic offloading through D2D communication.**

I. Introduction

Monthly global cellular traffic is predicted to surpass 24.3 exabytes by 2019 [1]. Traditional ways of improving cellular capacity to meet such a surging demand confront two major challenges. *First*, increasing the capacity of cellular links becomes difficult, not only due to the scarcity of spectrum, but also since the physical-layer technologies in LTE networks (such as MIMO-OFDM with capacity-achieving codes, multiple-antennas, and interference coordination) have approached the theoretical limits of spectral efficiency. *Second*, decreasing the cell size by deploying femto-cells is a feasible, yet *costly*, approach for improving the throughput of cellular networks, due to the cost of high-speed backhaul connectivity across femto-cell base stations.

With the looming possibility of a fundamental mismatch between bandwidth demand and supply, Device-to-Device (D2D) communication has recently attracted extensive research attention, due to its unique ability to offload cellular traffic, improve network throughput and energy efficiency. In essence, cellular traffic may be offloaded by D2D communication when mobile devices request different *pieces of content*, referred to as *messages* in this paper, over cellular networks. Through D2D communication, the traffic to transmit messages no longer traverse base stations and other components in LTE networks. Relieving an LTE network from some of its traffic-carrying responsibilities will increase its effective capacity. The interest for messages is both *time-dependent* and *location-sensitive*. For instance, passengers are likely to read the same time-limited coupon posted in a subway station, and access its related website within a short period of time. With the assistance of D2D communication, if a message happens to be read and cached at a device, it can then be retrieved by a neighboring device without consuming the bandwidth of links that interconnect base stations and other components in LTE networks.

The previous literature has largely focused on how D2D communication can run efficiently as an underlay to cellular networks [2] [3] [4]. In contrast, we focus on how D2D communication can effectively offload cellular traffic, with three major challenges. *First,* it is infeasible to cache all the messages a device has acquired due to its limited storage. A decision on whether to cache a message needs to be correctly made so that a limited number of cached messages can best meet local demand. *Second,* for each message being requested, there may be multiple devices that can send this message; for each device receiving requests, there may be multiple messages from which it can choose one to send. An algorithm that matches senders to receivers is needed to maximize cellular traffic offloading. *Finally,* being inherently selfish, mobile devices may not be willing to cache and share messages, since such caching and sharing will consume their local storage, energy, and uplink bandwidth. An incentive mechanism is inevitable for content sharing to proceed in practice.

In this paper, we propose *Rally*, a new array of strategies specifically designed to address these challenges, with the objective of maximizing cellular traffic offloading via D2D communication. As a highlight of this paper, the design of *Rally* is based on our theoretical analysis from a *game theoretic* perspective, where each mobile device is regarded as a selfish *player* in the game, and the D2D content sharing network is regarded as a *trading network*. With such a perspective, a D2D transmission can be naturally viewed as a trade, where the messages to be shared are treated as commodities, and the senders and receivers are viewed as sellers and buyers, respectively. The *price* of a message is the amount of profit a seller derives by trading the message, which is negotiated among local buyers and sellers. Through bargaining, prices of messages effectively reflect the demand and supply level of messages in the trading network. To fully motivate mobile users to participate in D2D content sharing, the base station pays monetary rewards to senders and receivers based on the price of a locally shared message. Such an infrastructure-driven framework distinguishes D2D content sharing from traditional ad hoc content distribution.

From a game theoretic perspective, we first show that the problem of maximizing cellular traffic offloading is equivalent to the maximization of social welfare in a trading network. We then proceed to divide the content sharing game as two subgames: a *non-cooperative caching game* where players make cache decisions based on market prices, followed by a *network formation game*, where players mutually select trading partners via a distributed bargaining process. Our bargaining strategy is designed by extending an existing bargaining dynamic [5], which guarantees a convergence to the Nash bargaining solution. The upshot of this paper from the perspective of game theory is our theoretical proof that, with our caching and bargaining strategies in *Rally*, the content sharing game converges to a subgame perfect Nash equilibrium. In a fully connected network, the social welfare, hence the cellular traffic offloading, is maximized at the Nash equilibrium point.

The remainder of the paper is organized as follows. We first present our system model and describe the content sharing problem in Sec. II. In Sec. III, we present the game theoretic formulation of the content sharing network. We proceed to present *Rally*, a set of strategies that constitutes a subgame perfect Nash equilibrium in Sec. IV. In Sec. V, we theoretically analyze the efficiency of our proposed strategies. Our simulation results in Sec. VI validate the effectiveness of *Rally*. We discuss possible extensions of our system in Sec. VII. We discuss our contributions in the context of related work in Sec. VIII before we conclude this paper in Sec. IX.

II. Content Sharing as a Problem

In this section, we present our system model, and formulate the D2D content sharing as an optimization problem. In general, we wish to offload cellular traffic by stimulating devices to cache selected messages locally, and by encouraging devices to retrieve messages from nearby devices rather than from the Internet. Our objective is to maximize such cellular traffic offloading.

A. System Model

We consider a single cell scenario, where a base station is responsible for relaying requests from each device to the Internet. Each device has a 3G or 4G interface for cellular network connections, as well as one interface for D2D communication. As our focus is on request-driven content sharing, we adopt unicast D2D as existing literature [6]. D2D communication operates on the licensed spectrum of the cellular operators and utilize LTE uplinks as defined in the infrastructure-driven model in the 3rd Generation Partnership Project [7]. Base stations lightly control D2D communication in terms of resource allocation, interference mitigation and authentication. Devices discover and communicate with each other through a signaling mechanism [8].

Leveraging the model of random geometric graphs [9], any two devices with a distance of at most R apart can communicate directly, and are neighbors. For a device d_i, we denote the set of its neighboring devices as N_i in Eq. (1).

$$N_i = \{d_j \in \mathcal{D} : ||d_i - d_j|| \leq R\} \tag{1}$$

where $\mathcal{D} = \{d_1, ...d_n\}$ denotes the set of devices randomly distributed in the cell.

Interference among D2D and cellular links is possible. Fortunately, the techniques for distributed resource allocation and link scheduling are already mature (*e.g.*, FlashlinQ [3]). Leveraging such a synchronous MAC/PHY architecture for D2D communication, we suppose D2D links have ignorable affect over cellular links, and mutual-interference among concurrent D2D links can be well handled. Nevertheless, two concurrent links at a device still conflict with each other. Choi *et al.* in [10] design a reliable transceiver to enable full-duplex communication. Based on their work, we suppose that each device can transmit and receive messages simultaneously, but at most one uplink and one downlink can exist. It then follows that a device can act both as a sender and a receiver at the same time, with the limitation that the sending and receiving procedure are both dedicated to another device respectively.

Since the storage capacities and battery lives of devices are limited, we stipulate that a device does not *prefetch* any message that it does not desire. We also impose the restriction that no messages are relayed over multiple hops. A device only assists its one-hop neighbors by sharing the messages it retrieved earlier. Furthermore, we assume each message is of unit size without loss of generality, since large messages can be divided into uniform-sized chunks when transmitted. Possible extensions to *Rally* are discussed in Sec. VII.

B. Problem Description

In a content sharing network, each device acts both as a message receiver and sender. As a receiver, a device tries to find a neighbor caching the message it desires. If fails, the request is re-sent to the base station. After a message is received, the receiver turns to a potential sender, and decides whether to cache the newly received message. As a sender, the device may receive multiple requests during a time period, but it can at most accept one request at a time. It is clear that each device makes two types of decisions: (1) which messages it should cache; and (2) which device it should communicate with. Our problem is to find the effective decision-making strategies to jointly maximize cellular offloading. With respect to caching strategies, each device estimates the *benefit* of caching a message. Although the access frequency is a plausible indicator [11], we argue that the local availabilities of messages is also necessary. With respect to selecting communication partners, receivers try to acquire messages at lowest possible costs, whereas senders try to earn profits from sharing. Devices must reach consensus on how to allocate the benefit of a D2D transmision to maximize their own profits.

For a more formal treatment of the content sharing problem, let $\mathcal{D}$ denote the set of devices randomly distributed in the cell. We introduce two sets of 0-1 variables x_{kj} and l_{ki}^j: x_{kj} equals one if d_k caches m_j; l_{ki}^j equals one if d_k sends m_j to d_i. The problem to maximize the weighted cellular offloading can be formulated as

$$\max \quad \sum_i \sum_j x_{kj} l_{ki}^j v_{ij} \tag{2}$$

$$\text{s.t.} \quad \sum\nolimits_j x_{kj} \le |C_k|, \quad \forall d_k \in \mathcal{D} \tag{3}$$

$$\sum\nolimits_j \sum\nolimits_{d_i \in S_j, d_k \in B_j} l_{ik}^j \le 1, \quad \forall i \tag{4}$$

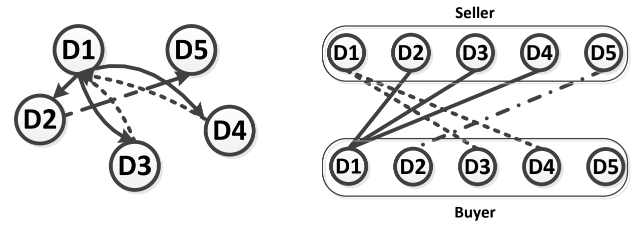
$$\sum\nolimits_j \sum\nolimits_{d_i \in B_j, d_k \in S_j} l_{ki}^j \le 1, \quad \forall i \tag{5}$$

The constraints (3), (4), (5) hold for every single device. More specifically, constraints (3) require the total cached messages never exceed a device's cache capacity. Constraints (4) and (5) avoid self-interference. For each message m_j, we define the set of players caching m_j as S_j, and the set of players requesting m_j as B_j. v_{ij} indicates the value of m_j for d_i, which is positively related to the local energy consumed or the cellular traffic incurred when transmitting m_j from the base station to d_i. A device itself estimates the value of a message and reports to the base station. Since the values of messages are input to the caching and bargaining algorithms, the definition of the valuation function has no influence on the design of algorithms. Due to the non-linearity of the content sharing problem, we utilize a game theoretic approach instead of leveraging combinatoric analyses.

III. Content Sharing as a Game

In this section, we regard each device as a rational player, and all the players in the network compose a local community. We formulate such a content sharing community as a trading network, where messages are goods, and senders and receivers are sellers and buyers, respectively. The following three observations motivate such a formulation. *First*, whether a device can receive a message locally depends on the number of its neighbors. Analogously, the number of sellers that a buyer can trade with determines the trading outcome. *Second*, since sharing is resource-consuming, devices are unwilling to share messages for free; they need to get paid in return. *Third*, the sharing of messages from senders to receivers is inherently similar to the flow of goods from sellers to buyers in a trading network [12].

In a trading network, the payoff for a buyer is the valuation of a commodity minus its price, and the payoff for a seller is the price of a commodity. Players choose to conduct a transaction only if the resultant payoffs are positive. Buyers in a D2D network, however, are unwilling to pay extra money to sellers, since they have already pay the cellular operators for mobile data services. It is thus the responsibility of cellular operators to stimulate D2D content sharing. To motivate players, the base station rewards a seller and a buyer by paying them the amount of money proportional to their payoffs in a successful D2D transmission. The monetary payoffs of a seller and a buyer add up to the monetary valuation of a message, which is proportional to a message's value. Sellers and buyers reach consensus on how to allocate the monetary values of messages through bargaining. Noticeably, the base station is always a backup seller to any buyer in the network and sell a message at a price equal to its valuation. In other words, the payoff of obtaining messages from the base station is always zero for a buyer. Therefore, a buyer chooses the base station as the seller only if the payoffs of D2D transmissions become non-positive.



(a) Content Sharing Network (b) Bipartite Exchange Market

Fig. 1. A content sharing network and its bipartite exchange market.

The utility function of a player is the payment earned from the base station through one local transaction. Since each player can be both a seller and a buyer, the utility function of a player can be represented in Eq. (6). We suppose the scaling factor for computing the monetary payments is one without loss of generality.

$$u(d_i) = \sum_{d_i \in S_j} \rho_{ij} \mathcal{P}_{kj} + \sum_{d_i \in B_j} \tau_{ij} (v_{ij} - \mathcal{P}_{ij}) \tag{6}$$

$$\rho_{ij} = \sum\nolimits_{d_k \in B_j} l_{ik}^j, \quad \tau_{ij} = \sum\nolimits_{d_k \in S_j} l_{ki}^j \tag{7}$$

ρ_{ij} and τ_{ij} indicate whether d_i has succeeded in selling and buying m_j locally. $\mathcal{P}_{kj}$ and $\mathcal{P}_{ij}$ are the transaction prices at which d_i has successfully sold and bought m_j, respectively. When a device first joins a cell, its utility is set to zero. As it starts to utilize D2D communication, it gradually accumulates its utility. Devices in a cell rely on the base station for authentication and accounting of individual utilities. A lightweight protocol described in [13] can be utilized to allocate payoffs to the senders and the receivers of successful D2D transmissions. The transaction price of a message is broadcast to the neighborhood once the transmission completes.

It is clear to see players go through two stages in content sharing. First, all players, acting as potential sellers, try to cache the most profitable messages. Second, all the sellers and buyers mutually select partners to trade with, trying to maximize their payoffs. Therefore, we divide the content sharing game into a non-cooperative caching game and a network formation game.

In a content sharing network $G_0 = (\mathcal{D}, E)$, a directed edge (i, j) exists if d_j, a neighbor of d_i, holds the message d_i requests (shown in Fig. 1(a)). In the caching game, the caches of all the potential senders form the supply of a bipartite exchange market $G = (B \cup S, E'), B = \bigcup_j B_j, S = \bigcup_j S_j$ (shown in Fig. 1(b)). An undirected edge in G is constructed as

$$e = \{i, k\} \in E', \text{ iff } (k, i) \in E, \ d_k \in B_j, d_i \in S_j \tag{8}$$

S_j includes the potential sellers of the message m_j, and its buyers comprise B_j. The neighboring vertices in G represent a player's potential partners. In the network formation game, players bargain with their potential partners on messages' prices. In accordance with the constraints (4) (5), players have to obey the *1-exchange rule*, namely, a player can at most select one neighbor as a trading partner. After the bargaining terminates, the trading network is formed and the messages are shared between trading partners. We adopt the *utilitarian social welfare function*, *i.e.*, the sum of individual utilities:

$$\text{Social Welfare} = \sum_i u(d_i) = \sum_i \sum_j \tau_{ij} v_{ij} \tag{9}$$

When some player d_k sells m_j to d_i, τ_{ij} and ρ_{kj} are equal to one, the utilities of d_i and d_k increase by $v_{ij} - \mathcal{P}_{ij}$ and $\mathcal{P}_{ij}$, respectively. The social welfare increases by v_{ij}. It is clear that the social welfare of the D2D network arises from the value of the offloaded messages. Therefore, maximizing the social welfare is equivalent to maximizing the weighted cellular offloading.

IV. Convergence to a Nash Equilibrium

In this section, we present a set of strategies, *Rally*, to construct a *subgame perfect Nash equilibrium* to the content sharing game. Specifically, we design the caching strategy that constitutes a Nash equilibrium to the non-cooperative caching game, and the bargaining strategy that results in a stable trading network in the network formation game.

A. Non-cooperative Caching

In a non-cooperative caching game, players act as potential sellers, and try to maximize their payoffs from their cached messages. As each message is of unit size, the cost to store and transmit any message is identical. It then follows that players can ignore the cost of caching and sharing, and only focus on the payoff a message can bring about. The profit of caching a message is thus the market price of a particular message.

The market price of a message, however, varies with its dynamic demand and supply status in the local market. At the current time t, after all the transactions in the local market complete, a message is sold at different transaction prices. The player d_i computes the local market price $\mathcal{P}_{ij}^t$ for the message m_j in Eq. (10). N_i is d_i's neighbor set and τ_{kj} is defined in Eq. (6).

$$\mathcal{P}_{ij}^t = \sum_{d_k \in B_j \cap N_i} \frac{(1-\tau_{kj})v_{kj} + \tau_{kj}\mathcal{P}_{kj}^t}{|B_j \cap N_i|} \tag{10}$$

Essentially, $\mathcal{P}_{ij}^t$ is the average of all the prices at which d_i's neighbors bought m_j at the current time t.

Prices reflect all past market information and instantly change to reflect new status. Therefore, players can estimate the future market price of a message based on its local transaction records. Each player records $\mathcal{P}_{ij}^{t-1}$ and $\mathcal{P}_{ij}^t$ for each cached message m_j, while the local market price at $t+1$ is estimated as

$$\mathcal{P}_{ij}^{t+1} = \max(0, \min(v_{ij}, \mathcal{P}_{ij}^t + \mu \triangle \mathcal{P}_{ij}^t)) \tag{11}$$

where $\triangle \mathcal{P}_{ij}^t = \mathcal{P}_{ij}^t - \mathcal{P}_{ij}^{t-1}$ and $\mu \in [0,1]$. In Eq. (11), the estimated price of a message is the linear combination of its current price and the difference between its current and last prices. The potential profit of m_j is thus $\mathcal{P}_{ij}^{t+1}$. Each player then chooses to cache the messages that are most profitable in the near future. The caching strategy for all the players is described in Algorithm. 1.

Algorithm 1 Profit-driven Caching Strategy

```
1: Initialize μ; W_i ← |C_i|
2: Compute the current local market price P^t_ij for each
   candidate message m_j ∈ C_i ∪ M*
3: P^{t+1}_ij ← max(0, min(v_ij, P^t_ij + μ△P^t_ij))
4: Sort messages in the decreasing order of P^{t+1}_ij
5: for j' = 1 to |C_i| do                ▷ Others are kicked out
6:     if |m_j'| < W_i then
7:         W_i = W_i − |m_j'|            ▷ Update capacity
8:         C_i = C_i ∪ m_j'              ▷ Cache the message
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Based on the profit-driven caching strategy, a player always caches a newly received message until the cache is full. Afterwards, the player eliminates the least profitable message among the messages in the cache ($m_j \in C_i$) and the newly received m^* (line 2). It is obvious that players will not deviate from this strategy, since their potential profits would decrease consequently. It follows that the caching strategy constitutes a pure-strategy Nash equilibrium.

B. Formation of the Trading Network

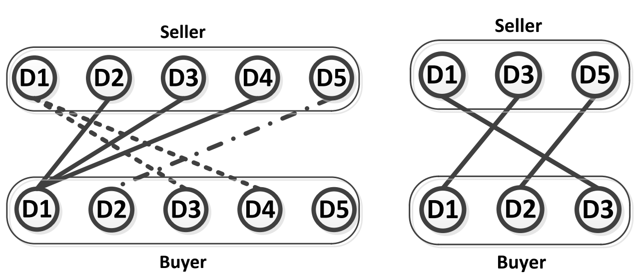
The trading network is built upon the bipartite exchange market G. Two players, d_i and d_k, connected by an edge $e = \{i,k\}$ in G are capable of trading with each other. Based on the *1-exchange rule*, each player needs to select only one as a trading partner. Suppose d_k requests m_j cached by d_i. The weight of the edge $\{i,k\}$, denoted as w_{ik}, equals v_{kj}. Since the payoffs for d_i and d_k add up to w_{ik}, the two players have a conflict of interest in how the profit of their transaction should be allocated. Therefore, bargaining is needed for the players to reach a consensus, and two players who conclude a bargain become trading partners. A set of valid trading partners forms a matching in G essentially. The goal to maximize the social welfare is thus equivalent to finding the maximum weighted matching in G.

A desirable bargaining outcome should be stable, balanced and Pareto optimal. The Nash bargaining solution is known to possess all these properties. The authors in [5] propose a bargaining dynamic, which is guaranteed to converge to the Nash bargaining solution. When the bipartite exchange market has a unique optimal matching, the convergence takes polynomial time. Otherwise, the convergence speed is *indeterminate*. We construct a perturbed graph $G_p = (B \cup S, E')$ with weights $\overline{w_{ik}} = w_{ik} + \eta U_{ik}$, where U_{ik} are independent random variables, uniformly distributed in $[0,1]$. The disturbance degree of the new weights is represented in $\eta \in [0,1]$. G_p has a unique optimal matching with high probability. Our bargaining strategy is shown in Algorithm 2.

Algorithm 2 Bargaining Strategy

1: Initialize $\overline{w_{ik}}$, ϵ, σ, $\alpha^0_{i\backslash k}$
2: **while** $|\alpha^r_{i\backslash k} - \max_{s\in N_i\backslash k} m^r_{s\to i}| \geq 2\epsilon$ **do**
3: Exchange best alternative $\alpha^r_{i\backslash k}$
4: $m^r_{i\to k} = (\overline{w_{ik}} - \alpha^r_{i\backslash k}) - \frac{1}{2}(\overline{w_{ik}} - \alpha^r_{i\backslash k} - \alpha^r_{k\backslash i})$
5: Calculate best earning $\lambda^r_i = \max_{s\in N_i} m^r_{s\to i}$
6: $\alpha^{r+1}_{i\backslash k} = (1-\sigma)\alpha^r_{i\backslash k} + \sigma \max_{s\in N_i\backslash k} m^r_{s\to i}$
7: **if** $\lambda^r_i = 0$ **then**
8: i fails to conclude a local transaction
9: **else**
10: $s = \text{argv}(\max_{s\in N_i} m^r_{s\to i})$, $(i,s) \in M$

Denote r as the index of the current round. The best alternative of d_i with respect to d_k is $\alpha^r_{i\backslash k}$, which represents the payoff d_i can get if it chooses to trade with a player other than d_k. d_i sends an offer $m^r_{i\to k}$ to d_k based on $\alpha^r_{i\backslash k}$ and $\alpha^r_{k\backslash i}$ (line 4). After receiving all offers, d_i updates the estimation of the best alternative as $\alpha^{r+1}_{i\backslash k}$, and sends to d_k. An inertia factor, $\sigma \in (0,1)$, is adopted to update the best alternatives. Sellers and buyers continue making new offers and new estimations until the difference between the estimated best alternative and the actual best alternative is less than 2ϵ. We further explain the bargaining process through the example in Fig. 2. d_1 is the only buyer of d_2, d_3 and d_4, which means $\alpha^r_{2\backslash 1}, \alpha^r_{3\backslash 1}$ and $\alpha^r_{4\backslash 1}$ all equal zero. The best alternatives for d_1 are positive since it has multiple potential senders. Therefore, the offers from d_2, d_3 and d_4 to d_1 keep increasing. The price of the corresponding message, in turn, keeps decreasing. d_1 can thus buy the message at a low price. Similarly, as d_3 and d_4 compete for a message cached in d_1, d_1 can sell the message at a high price. A possible trading network is presented in Fig. 2(b). From this example we can see the excess supply of a message pushes down its price, whereas a short supply pushes its price up.



(a) Bipartite Exchange Market (b) Trading Network

Fig. 2. The formation of a trading network.

Lemma 1. *After $r \geq O(\frac{n^2|E'|}{\eta\xi})$, the bargaining outcome of Algorithm. 2 converges to an ϵ-approximate Nash bargaining solution, which can induce the optimal matching of G with a probability of at least $1-\xi$, $\xi \in [0,1]$.*

Proof. See [5] for detailed proof. □

Theorem 1. *With our caching and bargaining strategies in* Rally*, the content sharing game converges to a subgame perfect Nash equilibrium.*

Proof. We have shown that the caching strategy constitutes a Nash equilibrium. Lemma 1 demonstrates that the bargaining outcome is the Nash bargaining solution, and the resultant trading network is stable, that is, the network formation game converges to a Nash equilibrium. Therefore, the content sharing game converges to a subgame perfect Nash equilibrium. □

V. Efficiency of the Game

A Nash equilibrium to a content sharing game is efficient only if it optimizes the social welfare of the network. Non-hierarchical network topologies, dynamic demand and selfish players are the main reasons for the inefficiency of a content sharing game. Theoretical analyses in hierarchical networks, such as tree and star networks, are tractable [14]. It is difficult, however, to analyze the efficiency of ad hoc networks. Moreover, the demand for a message, called its popularity, varies from time to time. For instance, requests for a piece of breaking news might emerge rapidly, leading to the severe shortage of that particular message. Consequently, many concurrent requests cannot be satisfied locally.

Given the intractability stated above, we investigate the scenario where devices are fully connected and the popularity distribution is static. We further prove *Rally* can maximize the social welfare under such conditions despite the selfish behavior of players. In a fully connected network, the transaction prices of messages are public to all players. Therefore, there exists a unique market price for each message in the network, namely,

$$\text{for } \forall\ d_i, d_k \in \mathcal{D}, \quad \mathcal{P}^t_{ij} = \mathcal{P}^t_{kj} = \mathcal{P}^t_j \tag{12}$$

Since all the players observe the same market price, the profits they estimate for each message are identical. As a result, the high profits of some messages stimulate the players to cache them. Such an emergence of affluent supply will saturate the markets quickly. Nevertheless, the supply of other messages is in shortage, making some of the requests locally insatiable. To mitigate the lagging regulation of the free market mechanism, the base station should guide players to maximize the social welfare without harming their profits. We introduce the *bonus* to regulate the caching behavior:

$$bonus = \sup_{d_i\in\mathcal{D},\ m_j\in\mathcal{M}} v_{ij} \tag{13}$$

As an incentive policy, the base station distributes the *bonus* to a player that caches the newly received message. It is obvious that the *bonus* is greater than or equal to the market price of any message. A newly received message is thus the most profitable among all the candidate messages. The profit-driven players would all cache their newly received messages immediately. We next prove there exists a *B-saturating* matching in the bipartite exchange market under the incentive policy.

Lemma 2. *There exists a matching in the bipartite exchange market with a cardinality equal to* $|B|$.

Proof. For $\forall \overline{B} \subset B$, $\overline{B} = B^t_{j_1} \cup B^t_{j_h} \cup ... \cup B^t_{j_H}$, where $B^t_{j_h}$ is the buyer set of m_{j_h} at the current time t. Driven by bonuses, the devices in $B^{t-1}_{j_h}$ all cache m_{j_h}, and become potential sellers of m_{j_h} at the time t. Namely,

$$B^{t-1}_{j_h} \subset S^t_{j_h} = N_G(B^t_{j_h}),\ \bigcup_h B^{t-1}_{j_h} \subset N_G(\overline{B})$$

where $N_G(B^t_{j_h})$ denotes the neighborhood of $B^t_{j_h}$ in G, *i.e.*, the set of all sellers adjacent to some buyer in $B^t_{j_h}$. Since the buyer sets, $B^{t-1}_{j_h}$, are non-overlapping, we have

$$|\bigcup_h B^{t-1}_{j_h}| = \sum_h |B^{t-1}_{j_h}|$$

Recall that the demand is static. It follows that,

$$|N_G(\overline{B})| \geq \sum_h |B^{t-1}_{j_h}| = \sum_h |B^t_{j_h}| = |\overline{B}|$$

According to *Hall's theorem*, there exists a matching in the bipartite exchange market with cardinality equal to $|B|$, which is called a *B-saturating* matching. □

In other words, there exists a trading network that satisfies all the requests locally. Under the incentive policy, the social welfare defined in Eq. (9) is recomputed as

$$\text{Social Welfare} = \sum_i \sum_j \tau_{ij} v_{ij} + |B| \cdot \textit{bonus} \qquad (14)$$

Since the demand for messages and the bonus are both static, $|B| \cdot \textit{bonus}$ is a constant term in Eq. (14). The maximization of the recomputed social welfare is thus still equivalent to maximizing the cellular offloading. Since player's caching strategy remains unchanged, it still constitutes a Nash equilibrium. We next show that the social welfare is maximized at the equilibrium point.

Theorem 2. *Social welfare is maximized at the Nash equilibrium point through the non-cooperative caching and the formation of a trading network.*

Proof. According to Lemma 2, the profit-driven caching strategy guarantees the existence of a *B-saturating* matching in the bipartite exchange market. Combined with Lemma 1, the bargaining process finds the optimal matching between sellers and buyers, which must be a *B-saturating* matching. It follows that all the requests for messages can be satisfied locally. In other words,

$$\tau_{ij} = 1, \quad \text{for } \forall\ d_i \in B_j,\ \forall\ m_j \in \mathcal{M}$$

$$\text{Social Welfare} = \sum_i \sum_j v_{ij} + |B| \cdot \textit{bonus}$$

Therefore, the social welfare is maximized after the content sharing game converges. □

When devices are partially connected, they merely have imperfect market information. On the one hand, the efficiency of the content sharing game is no longer guaranteed. On the other hand, devices become less likely to cache the same messages due to different local prices, and the extra bonus is thus *unnecessary*. Despite the hardness of theoretical analyses, we show through simulations that *Rally* still performs well in partially connected networks, even when the demand is dynamic.

VI. Evaluation

In this section, we evaluate the performance of the content sharing system based on a time-slotted simulator implemented using C++. The length of a time slot is one second. With a communication range between 70 and 140 meters, each device has 30 neighboring devices on average [15]. As our system model is independent of the valuation for messages, we assume that the values of all the messages are identical. The perturbed graph G_p in the network formation game is constructed with $\eta = 1$. According to Lemma 1, the bargaining process converges when $r \geq O(\frac{n^2|E'|}{\eta\xi})$. In practice, after 10-20 bargaining rounds, the outcome has already stabilized. Therefore, we set the number of total bargaining rounds as 10 to shorten the bargaining process.

It is commonly assumed the popularity of messages follows a *Zipf-like* distribution [16], where the relative probability of a request for the i^{th} most popular message is proportional to $1/i^{\alpha}$. The estimates of α typically range from 0.5 to 1 for web proxies, and range from 1 to 2 for a busy web server [17]. We vary α from 0.6 to 2 in our experiments. Furthermore, the size of a message is 512 KB, and there are 10,000 messages in the message repository. Each device independently sends a request with probability 0.5 in each time slot. We use the *cache hit ratio* and the *offloading ratio* to examine the effectiveness of *Rally*. The cache hit ratio is the percentage of requests that hit local caches, and the offloading ratio is the percentage of cellular traffic offloaded through D2D communication. We next evaluate *Rally*'s offloading performance, its agility to dynamic demand and its sensitivity to system parameters.

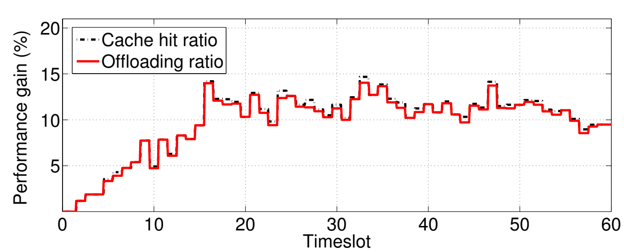


Fig. 3. System performance with the average cache capacity $|C_i| = 5$MB, $|N_i| = 30$, $m = 10,000$, $\alpha = 0.99$. The average offloading ratio over the 60 time slots is 9.55%.

A. Overall Performance

We first inspect the overall performance of a content sharing network over 60 time slots in Fig. 3. Since the caches of all devices are empty initially, the cache hit ratio and the offloading ratio both equal zero at first. Gradually, devices start to retrieve messages and cache the useful messages locally. After 16 time slots, the system performance stabilizes around

12%. The average offloading ratio over the simulation period is 9.55%.

Based on the statistic of all the local requests, about 72% of the requests are unique. In other words, the corresponding messages are only required once, making it impossible to acquire through D2D communication. Therefore, the optimal offloading ratio is at most 28% even if devices have unlimited cache capacities and the network is fully connected. Our system demonstrates its strong capability in alleviating the need for cellular bandwidth through D2D communication. Furthermore, we can see that the difference between the cache hit ratio and the offloading ratio is fairly small, which demonstrates the efficacy of our bargaining strategy.

B. Comparisons with Other Methods

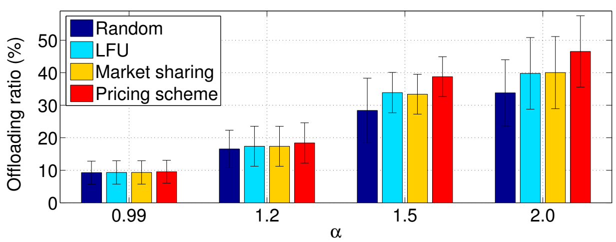


Fig. 4. The pricing scheme outperforms other three methods relatively by more than 2%, 6%, 16% and 17% when $\alpha = 0.99$, 1.2, 1.5 and 2. $|C_i| = 5$MB, $|N_i| = 30$, $m = 10,000$.

We conduct a series of experiments to compare the offloading ratios of four different caching algorithms in Fig. 4. As a benchmark, devices in the first group randomly replace messages when their caches are full. The second group applies the Least Frequently Used (LFU) approach, which greedily discards the least frequently accessed message. The third group of data is collected by using the market sharing mechanism proposed in [13], where devices who cache a message equally share the profit of this message. This method is similar to ours in that it also considers the supply of messages.

In the last group, we adopt the pricing scheme we have designed in this paper. As we can see from the results, the pricing scheme surpasses the other three methods under different popularity distributions. Furthermore, our solution is more effective when the redundancy of requests is higher: compared with the market sharing mechanism, our scheme relatively improves the offloading ratio by 2% and 6% when α equals 0.99 and 1.2, respectively; when α equals 1.5 and 2.0, our method outperforms other methods significantly, improving the offloading ratio by more than 16%.

C. Dynamic Response of the System

The dynamic response of our system to the variation of message requests is presented in Fig. 5. At the 30th time slot, the popularity distribution changes completely, which imitates the shifting of interest during different periods of a day. For instance, the most popular message might be a piece of breaking news during the morning, whereas the video

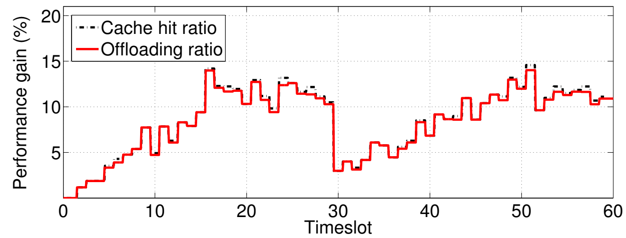


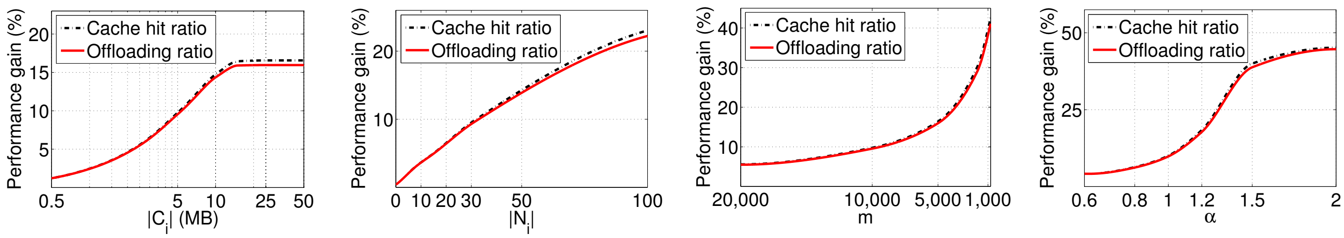
Fig. 5. Dynamic response to the variation of demand with $|C_i| = 5$ MB, $|N_i| = 30$, $m = 10,000$, $\alpha = 0.99$. The popularity distribution is updated when $t = 30$.

highlights of a basketball game might become popular in the evening. The result demonstrates that the content sharing system reacts quickly to any changes in demand under market regulations: within 12 time slots after the demand changes, the system performance goes back to normal. The key to such agile response is our pricing scheme makes local supply of messages keep up with any change promptly. If the requests for a message emerge rapidly, the original supply of this message becomes insufficient. Consequently, its market price increases dramatically, attracting more devices to cache it. On the contrary, if the requests for a message diminish over time, its original supply becomes ample. The market price of this message decreases gradually, making it less appealing to devices. In essence, the pricing scheme forms negative feedback and improves the dynamic response of the system.

D. Sensitivity Analysis

The basic parameters for sensitivity analysis are as follows: $|C_i| = 5$MB; $|N_i| = 30$; $m = 10,000$; and $\alpha = 0.99$. We vary one parameter each time, and keep the other parameters constant to analyze the influence of each system parameter. Fig. 6(a) illustrates that the offloading ratio significantly increases with larger cache capacities. The devices with larger capacities are able to store more messages. The local content availability thus arises, leading to better system performance. The slope of the curve, however, decreases with larger cache capacities. The most appropriate cache capacity could be adjusted based on different application scenarios. Similarly, when the local network intensifies, the content availability will raise. Fig. 6(b) shows that the offloading ratio keeps increasing with the increase of the average number of neighbors a device has. Nevertheless, D2D links are more likely to mutually interfere when the network is denser. It is therefore more difficult to schedule these links. A trade-off between offloading performance and system complexity needs to be considered.

In Fig. 6(c), it is clear to see that the offloading ratio decreases with the increasing number of messages. A larger repository implies that the interest for messages spreads more widely. In other words, it is less likely that the messages a device holds are appealing to other devices. Consequently, the possibility of finding a desired message locally becomes lower. Fig. 6(d) illustrates the system performance under different popularity distributions. When α increases, the offloading ratio



(a) Cache capacity. (b) Network density. (c) Number of messages. (d) Popularity distribution.

Fig. 6. Average offloading ratios and cache hit ratios under different system parameters.

improves accordingly. Among all the system parameters in Fig. 6, the offloading performance is most sensitive to α. Therefore, D2D content sharing is especially beneficial when the local requests are highly redundant.

VII. Discussions

In this section, we first discuss whether *Rally* applies to the situation where users are not static, but keep moving randomly across multiple cells. We then enable multi-hop D2D by involving devices as relay. Furthermore, we discuss how to apply our algorithms in a scenario where push-based broadcast communication is more efficient. Finally, we explain how our scheme deals with cheating.

Mobility: When users that hold mobile devices are static, each device has a fixed set of neighbors that it can communicate with. However, users actually move with different velocities and to different directions from time to time. Therefore, the neighbors of a device change accordingly. Under such circumstances, *Rally* still works if devices can dynamically discover and negotiate with their current neighbors. Furthermore, it is also possible that the sender is moving away from a receiver, which makes the signal between them decrease. Devices can detect such signal decrease and starts to find another potential partner. If the signal strength goes down below a threshold, the device would switch to the potential partner to continue receiving the message.

Multi-cell scenario: Our system can be easily applied to a multi-cell scenario if the base stations in different cells all support D2D communication. In fact, only devices reside in the border of a cell would be influenced. The major problem is how to enable devices from different cells to discover each other and who to allocate radio resources to such a connection. Once these problems are fixed, *Rally* can be naturally applied to devices in the cell borders without modifications.

Multi-hop D2D: If we enable multi-hop communication, a new type of players, traders, needs to be introduced. Players as traders do not need messages, they only want to earn profit by relaying messages from sellers to buyers. Traders must ensure the asked (selling) prices is higher then the bid (buying) price of any relayed message. As a result, there might be more bargaining rounds involved in one transaction. Traders first set prices based on local information, buyers and sellers then react to these prices accordingly [12] [18].

Push-based broadcast: For pull-based content retrieving, unicast is appropriate; for push-based message spreading application, such as public safety services and mobile advertising, broadcast fits more [19]. Under such circumstances, a message source is fully motivated to spread messages, while receivers prefer to receive messages locally due to less power consumption. Therefore, no incentive mechanism is necessary. The problem shifts to scheduling who should send out messages to avoid interference and improve information coverage [20]. As the application scenario of push-based broadcasting is totally different from pull-based content sharing, we do not employ D2D broadcast in our content sharing system. For future work, we can design a hybrid D2D network to enable both unicast and broadcast by introducing a two-layer game. In the first layer, buyers requesting the same message are regarded as one super-buyer, and participate in the bargaining process as a single entity. In the second layer, buyers determine individual payments through negotiation.

Potential cheating: The rewarding mechanism in *Rally* encourages devices to help each other through D2D communication. Unfortunately, such a mechanism does not necessarily stimulate people that holding the devices to help each other. Since users may have multiple devices, a user can make his or her own devices send messages to each other. Without knowing this, the base station will pay both the sender and the receiver. These devices can then retrieve messages from devices belonging to other users without actually contributing to them. Most existing P2P-like systems suffer from such a risk since it is almost impossible to directly determine whether multiple devices belong to the same user. We can only try to identify such malicious devices by checking the communication pattern of each device. For instance, if a set of devices only frequently communicate with each other, these devices will form a coalition. If the devices in this coalition only have incoming links (downlinks), they probably belong to a malicious user. We leave such a detecting mechanism for future work.

VIII. Related Work

The cooperative caching problem has been widely studied in wireless ad hoc networks. To maximize content accessibility, the caching algorithm proposed in [11] leverages the access frequency of messages. Merely focusing on the demand of messages, such a mechanism fails to consider distinct message supply in the neighborhood. We propose a pricing scheme for devices to fully utilize their storage to best meet dynamic and unforeseen local demand. Secondly, this method, as well as a substantial amount of other works (*e.g.,* [21], [22]), impose caching and sharing as compulsory services that devices have to provide, ignoring the costs to prefetch and share messages. Essentially, devices make selfish decisions based on their resource restrictions.

Chun *et al.* first solve the selfish caching problem in [23]. They simplify the problem by unrealistically assuming devices have unlimited storage capacities. Goemans *et al.* in [13] formulate the caching problem as a market sharing game, where the profit of caching a message is proportional to the number of requests for each message, and inversely proportional to the number of devices that cache this message. Choi *et al.* in [24] try to determine the degree of selfishness of a device to help senders to adjust their strategies accordingly. Lacking of actual rewarding from a central coordinator, these *tit-for-tat* mechanisms merely exclude free riders. With the base station actively stimulating devices in *Rally*, mobile users are willing to cache, share and receive content through D2D communication for monetary payoffs.

Chen *et al.* in [25] propose a social trust and social reciprocity based method for devices to form coalitions and select relay devices, while the sender-receiver pairs are fixed. Abedini *et al.* tackle the sender selection problem in broadcast D2D applications [20]. Their focuses are both different from ours in that we enable senders and receivers to mutually select each other to maximize mobile user profits and cellular traffic offloading simultaneously. Henceforth, their works are orthogonal to ours, and can be utilized if multi-hop and broadcast D2D communication is considered.

IX. Conclusion

In this paper, we have studied the content sharing problem through D2D communication with the objective of maximizing cellular traffic offloading. We present an in-depth analysis on content sharing from a game theoretic perspective. The content sharing game consists of a non-cooperative caching game and a network formation game. In the caching game, each mobile device makes cache decisions driven by their own profits in a non-cooperative way. In the network formation game, we propose a bargaining strategy for devices to select their optimal trading partners in polynomial time. The results from both theoretical analyses and extensive simulations demonstrate that *Rally* can offload cellular traffic effectively, even when the demand for messages changes over time.

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