Peer-assisted Data Offloading and Distributed Channel Selection for Mobile Cloud Computing

Yongan Guo[1], Dapeng Li[2,3] , Ze Jiang[2], Feng Tian[2]

[1] Jiangsu Key Lab of Wireless Communications, Nanjing University of Posts and Telecommunications, China
[2] Jiangsu Engineering Research Center of Communication and Network Technology,
Nanjing University of Posts and Telecommunications, China
[3] National Mobile Communications Research Laboratory, Southeast University, China
{guo, dapengli, zjiang, ftian}@njupt.edu.cn

Abstract

The rapid growth of intelligent applications makes it increasingly desirable to offload mobile terminals (MTs) traffic to data centers for smart computing. In this paper, we propose a distributed channel selection scheme with cooperative offloading, in which MTs help each other in each channel to offload the data for the purpose of saving energy. Particularly, MTs that are in the same channel and close to each other in a certain geographical area can form into cooperation cluster to perform local computing, then, offload the data to a cloud server in a certain wireless channel. In this way, the energy consumption for data offloading can be reduced. We adopt game theory to formulate the channel selection problem as a non-cooperation game. We then prove that the formulated game is a potential game, and, thus, guarantee the existence of Nash equilibrium. A Markov approximation approach is then applied to design a distributed channel selection algorithm so that each MT can self-organize into stability without information exchange across the whole network. Analytical and numerical results show that the distributed algorithm is efficient in comparison to the centralized optimization solutions.

Keywords: Collaborative mobile network, Mobile data offloading, Game theory, Nash equilibrium

1 Introduction

The fast-growing smartphone techniques and rapidly increasing volumes of mobile data traffic are continually enriching our experience with mobile applications as well as changing our daily lives. However, the demand for high-data rate mobile services will drain the batteries of devices much faster than before [1]. In particular, energy conservation has been one of the most challenging design issues for mobile devices [2-3]. Because of their limited physical size, mobile terminals (MTs) are often equipped with a limited supply of resources in terms of computation, energy, bandwidth and storage etc. As a result, offloading the computation tasks from mobile devices to cloud servers is considered as potential solution to conserve battery life [4-6].

According to the diversity of the data offloading, the survey work [7] has classified the data offloading techniques into several categories, i.e., data offloading through small cell networks [8], mobile agent networks [9], or edge computing, respectively. Specifically, for IoT applications, such as smart cities, the smart grid, smart traffic lights, and smart vehicles, the data processing capabilities are pushed to the edge of network devices with the integration of EC [10]. In [11], the authors devise a resource-efficient. edge computing scheme such that an intelligent IoT device for support its computationally intensive task by proper task offloading across the local device and nearby helper device. A NOMA based optimization framework was proposed in [12] to minimize the energy consumption of edge devices via the clustering resource allocation. A joint resource allocation and offloading scheme is designed in [13] through solving a two-dimensional knapsack problem for a MEC based vehicular networks.

Different mobile data offloading approaches have also been studied to address energy saving problems in previous works. The authors in [14-18] proposed different novel frameworks for WiFi offloading to decrease waiting times or promote the efficiency of data offloading. In order to improve the energy efficiency, mobile applications can be either executed in the mobile device or offloaded to the cloud clone for execution according to data sizes, deadline time and the channel state [19]. The task scheduler model at the centralized broker based on task-related or user-defined constraints optimally offloads tasks and provides significant reductions in energy consumption. The authors in [20] developed energy-efficient computation offloading algorithms for cellular

*Corresponding Author: Dapeng Li; E-mail: dapengli@njupt.edu.cn
DOI: 10.3966/160792642019092005014

networks. They analyzed the effects of the long tail problem on task offloading and used Dijkstras algorithm to generate the optimal decision. Moreover, the authors in [21-23] combined energy harvesting technologies with data offloading to improve the energy efficiency. In [24], the authors proposed a multiobjective dynamic programming approach to minimize the estimating cost while satisfying latency requirements with best effort. These works considered single-MT data offloading schemes and used optimization methods to improve energy efficiency.

Many works have been proposed to improve energy efficiency via user cooperation in wireless networks. The authors in [25] proposed a novel approach for allowing the small cells to cooperate to optimize their sum-rate under transmit power constraints. The authors in [26] developed an algorithm to allow the MTs to choose coalition groups to download the content from the BS and either unicasts or multicasts it to the other MTs. [25] and [26] considered cooperation models based on physical interferences while not accounting for data offloading scenarios. In [27-28], the authors investigated the problems of designing content sharing collaborative mobile cloud (CMC) via user cooperation to reduce the energy consumption at the terminal side for the scenario where a group of users interested in receiving the same content from an operator. The work [29] has designed a job scheduler running on mobile-cloud computing platforms to generate an optimized job schedule for a distributed app, rather than analyze the cooperation between peer nodes.

A device-level information centric networking architecture is proposed in [30] to perform intelligent content distribution operations according to necessary context information for MTs. In [31], the authors proposed D2D big data platform to encourage wireless device-to-device communications, thereby carrying out offloading intelligence for operators efficiently. For offloading vehicular communication traffic in the cellular networks, a software-defined network (SDN) with the mobile edge computing (MEC) architecture is proposed in [32] to uses each vehicle's context and set up a V2V path between the two vehicles for notification. The above works mainly focus on large scale content delivery probability, but not account for the energy-efficient computation offloading.

A peer-Assisted computation offloading framework is proposed in [33] to enable a client experiencing poor service quality to choose a neighbor as the offloading proxy helper. Through WiFi interface, the node can offload computation tasks to the helper, then, further transmits the task to the cloud server through cellular links. However, the scheme leverages peers with better service quality for computation offloading, thus, ignore the fairness issues. Thus, it may not be a stable solution in a decentralized setting. Also, the work does not consider the wireless channel selection problem, thus, cannot capture the bandwidth characteristics for peer-assisted computation offloading.

The game theoretic models have often been used to study non-cooperative behaviors for mobile offloading. In [34], the authors consider a market game model where MNOs lease APs that are already deployed by residential users for the offloading purpose. The work [35] studies a non-cooperative game model where the uses share the limited computing resources, and a generalized Nash equilibrium solution is obtained. The computation offloading strategy of multiple users via multiple wireless Aps is investigated in [36], where the authors design a distributed computation offloading algorithm to help mobile users choose proper offloading strategies by introducing the definition of a potential game. In [37], the authors study the computation offloading strategy in a multi-channel wireless interference environment, in which the users will cause interference with each other in the same channel to perform the independent data offloading task. Although the potential structural properties are considered in [36-37], those works do not consider the cooperation between peers. In this paper, we will formulate the channel selection process with the peer-assisted offloading as a potential game, and a Markov approximation approach is also introduced to design the distributed channel selection algorithm.

The main contribution of this paper is to propose a peer-assisted computation offloading scheme with the distributed channel selection in order to minimize an MT's energy consumption cost. The round robin scheme is used to guarantee the fairness among the MTs in each channel. More specifically, each MT in this context chooses a channel in up-links to form a coalition according to the offloading data size and the distance to other MTs. We formulate the channel selection problem as a potential game and design a distributed channel selection algorithm by using a Markov approximation approach, to design a distributed channel selection algorithm for MTs to achieve the Nash equilibrium of the game. MTs can self-organize into stable groups and only require the information exchanges of MTs in the same channel. Our contributions in this paper are summarized as follows:

- We propose a cooperative data offloading model, with jointly considering the distributed channel selection. The proposed scheme enables mobile devices to help each other in proximity to perform the computing task and offload the data in a certain channel. Our formulation can capture the essentials of the cooperative users' offloading data sizes and also account for the state of up-links between each other user.
- We then formulate the channel selection problem as a pure strategy game and prove that the formulated game is a potential game and thus has a pure Nash equilibrium.
- Using Markov chain principles, we propose a

distributive channel selection algorithm for the model in this paper. In each channel, MTs can self-organize into a stable group to promote energy efficiency.

The remainder of this paper is organized as follows. In Section 2, we present the system model and formulate it as a distributed channel selection game. In Section 3, we demonstrate that the proposed pure strategy game is a potential game and thus can achieve Nash equilibrium. In Section 4, we propose a distributed channel selection algorithm based on local energy consumption observations that can converge to the Nash equilibrium. Section 5 presents the numerical results in terms of the efficiency of the algorithm and an energy consumption comparison between the centralized solution and the distributed algorithm. The theoretical and numerical results show that the algorithm that we introduced is efficient and feasible in a collaborative mobile network context. Part of this work has been presented in [38].

2 System Model and Problem Formulation

2.1 System Model

We consider a set of MTs $\mathbf{N} = \{1,...,N\}$ geographically close to each other that desire to offload their computation intensive data to servers in the cloud via base stations (BSs). Let $\mathbf{M} = \{1,...,M\}$ denote the set of wireless channels. $\mathbf{a} = \{a_1, a_2, ..., a_n\}$ is the channel selection vector of the MTs. Define Θ is the strategy space of $\mathbf{a}$.

Each MT will attempt to access individual channels to offload an amount S_i of data directly through long-links to the base station. This will lead to a high transmit power when the data size is too large. Moreover, the distance between the BS and the MT is often up to several kilometers. In this paper, we study the collaborative data offloading with channel selection for mobile edge computing. In the proposed scheme, MTs choose a channel according to the distributed channel selection algorithm; then, the MTs in the same channel perform data offloading in a cooperative way. The proposed scheme consists of the following steps as shown in Figure 1 and Figure 2:

- Step 1: A header will be chosen randomly from the MTs in the same channel, and the other MTs transfer data to the header via short links(e.g., WiFi or Bluetooth).
- Step 2: The header executes a data offloading task to transmit all the data collected from other users in the same channel to the BS through a long link.
- Step 3: Every MT in the same channel acts as the header in turn. To guarantee fairness, we assume that each header works for a same time duration. Return to Step 1.

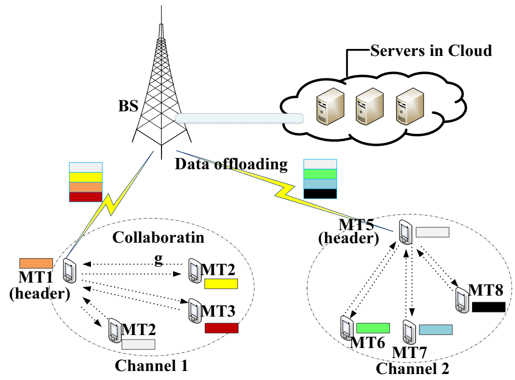


Figure 1. System Model. MTs assist each other to offload computation-intensive data to the cloud server via the BS. MTs in the same channel worked as headers in turn. The servers in the clouds complete the offloaded tasks and return the results

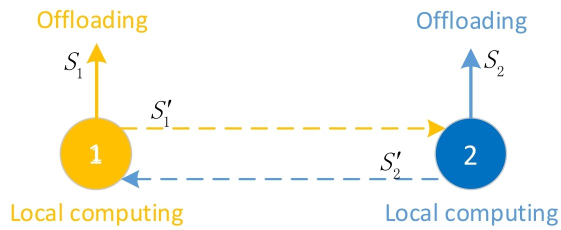


Figure 2. MT1 forward some date via short link to the neighbor/header node then the header performs some simple computation locally then offloads the data to the server.

Our scheme can be implemented periodically to enable MTs to form stable coalitions, then, perform collaborative offloading. Thus, the three steps can repeat periodically in practice. And, the role of each node can be decided by the protocol of the MAC layer, or be scheduled by the BS. The proposed scheme can reduce unnecessary energy consumption caused by long-link transmissions and hence can improve the energy efficiency. The main notations of the paper are summarized in Table 1.

Table 1. Notation table

Symbol	Definition
a_i	The channel selection strategy of MT i
P_{ni}	The transmission power from MT n to i
P_n^l	The transmission power of offloading for MT n
D_n	The transmission distance from MT n to BS
D_n^α	The pass loss for the transmission of D_n
d_{ni}	The transmission distance from MT n to MT i
d_{ni}^α	The pass loss for the transmission of d_{ni}
S_i	The amount of offloading data for MT i
S_n'	The amount of data of MT n for assisted-computing
$E_{offloading}$	The energy consumption of offloading for MT n
E_{co}	The energy consumption of cooperative transmission for MT n

We denote the energy consumption of MT n in the offloading phase through a long link as $E_{offloading}$, which can be expressed as

$$E_{offloading} = \sum_{i \in N} \frac{P_n^l}{R_n^l} S_i \cdot I\{a_i = a_n\} \quad \textbf{(1)}$$

where P_n^l is the long link transmission power of MT n, R_n^l is the long link transmission rate, and I{·} is an indicator function such that {·} = 1 if the event {·} is true and {·} = 0 otherwise. According to Shannon's theorem, we have

$$\mathrm{R}_n^l = W_l \log_2(1 + \frac{P_n^l D_n^\alpha}{\sigma^2}) \quad \textbf{(2)}$$

where W_l is the channel bandwidth of the long transmission link, D_{n} is the long distance from MT n to the BS, σ^2 is the Gaussian noise power, and α is the path loss factor. In the cooperation phase, each MT can be a cooperative member for transferring its own data to the header. Therefore, for MT n, the energy consumed in the cooperation phase can be represented as

$$E_{co} = \sum_{i \in N, i \neq n} P_{ni} \frac{S_n'}{R_{ni}^s} \cdot I\{a_i = a_n\}, \quad \textbf{(3)}$$

in which we denote the transmission power from MT n to MT i($i \in \mathbf{N}$, $i \neq n$) as P_{ni} . R_{ni}^s is the short link transmission data rate from MT n to MT i. Similarly, for the short link, we have the following expression based on
Shannon's theorem:

$$\mathrm{R}_n^{\mathrm{s}} = W_s \log_2(1 + \frac{P_{ni} d_{ni}^\alpha}{\sigma^2}), \quad \textbf{(4)}$$

where W_s is the channel bandwidth of the short transmission link and d_{ni} is the distance between MT n and MT i. In this context, we consider the total energy consumed by the MT in all cases. Taking the sum of the energy consumed in both the offloading and cooperative phases as MT n's utility function, we can obtain

$$\begin{aligned} E_n &= E_{offloading} + E_{co} \\ &= \sum_{i \in N} \frac{P_n^l}{R_n^l} S_i \cdot I\{a_i = a_n\} \\ &+ \sum_{i \in N, i \neq n} P_{ni} \frac{S_n'}{R_i^s} \cdot I\{a_i = a_n\} \\ &= \sum_{i \in N} \frac{(2^{\frac{R_n^l}{w_l}-1})\sigma^2 D_n^\alpha}{R_n^l} S_i \cdot I\{a_i = a_n\} \\ &+ \sum_{i \in N, i \neq n} \frac{(2^{\frac{R_n^l}{W_s}-1})\sigma^2 d_{ni}^\alpha}{R_{ni}^s} S_n' \cdot I\{a_i = a_n\} \end{aligned} \quad \textbf{(5)}$$

2.2 Problem Formulation

In this coalition framework, each user will choose a proper channel to minimize its own energy consumption. Therefore, the objective function of MT n is

$$\underset{\{a_1, a_2, \ldots, a_n\}}{\mathrm{Min}} E_n, n \in \mathbf{N}. \quad \textbf{(6)}$$

Function (6) is a joint optimization problem, in which each MT's objective function is associated with other MTs' strategies. Different channel selection strategies **a** of the MTs can lead to different energy consumptions E_{n} of MT n. To the best of our knowledge, problem (6) is very challenging to solve. Therefore, we now consider the distributed channel selection problem among MTs via a game theory approach. Let $\mathbf{a}_{-n} = \{a_1, a_2, \ldots, a_{n-1}, a_{n+1}, \ldots, a_N\}$ be the set of channels selected by all the other MTs except MT n.

Now, we can formulate the channel selection problem among MTs as a non-cooperative game where the utility function of MT n is given by the negative energy consumption function of MT n:

$$\begin{aligned} \mathrm{U}_n(a_n, a_{-n}) &= -E_n \\ &= -\sum_{i \in N} \frac{(2^{\frac{R_n^l}{w_l}-1})\sigma^2 D_n^\alpha}{R_n^l} S_i \cdot I\{a_i = a_n\} \\ &- \sum_{i \in N, i \neq n} \frac{(2^{\frac{R_{ni}^s}{w_s}-1})\sigma^2 d_{ni}{}^\alpha}{R_n^l} S_n' \cdot I\{a_i = a_n\} \end{aligned} \quad \textbf{(8)}$$

The solution concept of such a channel selection non-cooperative game is Nash equilibrium defined in the following.

Definition 1. For the proposed channel selection game, the strategy profile $\mathbf{a}^* = \{a_1^*, a_2^*, \ldots, a_N^*\}$ is called Nash equilibrium if and only if,

$$U_i(\mathbf{a}^*) \geq U_i(a_i^*, a_{-i}), \forall a_i \in \mathrm{M}, \quad \textbf{(9)}$$

which means that, for each player i, a_i^* is the est response strategy to other players' strategies $\mathbf{a}_{-i}^*$. In other words, under the condition of Nash Equilibrium, any player in the game cannot change their own strategy unilaterally to improve their utility.

$$a_n^* = \arg\max_{a_n \in \mathrm{M}} U(a_n, \mathbf{a}_{-n}^*), \forall n \in \mathrm{N} \quad \textbf{(10)}$$

In what follows, this paper attempts to find the Nash equilibrium $\mathbf{a}^*$ of the formulated game in a distributed way, by using the potential properties of the proposed game. The main notations are listed in Table 1.

3 The Potential Property of The Proposed Game

Based on the previously described channel access game, we now study the existence of the Nash Equilibrium of the game. Here, we resort to a useful tool of potential games [39]. Toward this end, we first show that for the above utility function (8), we can formulate a potential function that enables the game to converge to a pure strategy Nash equilibrium solution.

In game theory, a game is said to be a potential game if the incentive of all players to change their strategy can be expressed using a single global function called the potential function. The potential function models the information associated with the improvement paths of a game instead of the exact utility of the game.

Definition 2. A game is called a potential game if it admits a potential function $\Phi(\mathbf{a})$ such that for every $n \in \mathbf{N}$,

$$\begin{aligned} &\mathrm{sgn}(U_n(a_n', \mathbf{a}_{-n}) - U_n(a_n, \mathbf{a}_{-n})) \\ &= \mathrm{sgn}(\Phi(a_n', \mathbf{a}_{-n}) - \Phi(\mathrm{a}_{\mathrm{n}}, \mathbf{a}_{\text{-n}})). \end{aligned} \tag{11}$$

$$\mathrm{sgn}(x) = \begin{cases} 1 & x > 0 \\ 0 & x = 0 \\ \text{-}1 & x < 0 \end{cases}$$

A nice property of the potential game is that it always admits a Nash equilibrium, and any strategy profile that maximizes the potential function $\Phi(\mathbf{a})$ is a Nash equilibrium [35]. For the proposed game, we can show that it is a potential game with the following potential function:

$$\begin{aligned} \Phi(\mathbf{a}) = &-G_1 \sum_i \sum_{j \neq i} D_n^{2\alpha} S_i S_i \cdot I\{a_i, a_j\} \\ &- G_2 \sum_i \sum_{j \neq i} S_n'^2 D_n^\alpha d_{ij}^\alpha \cdot I\{a_i, a_j\} \end{aligned} \tag{12}$$

in which we introduce G_2, G_2 as the notation for the constant term because R_n^l, R_{ni}^s, W_l, W_s are set to constant values in this context, where

$$G_1 = \frac{(2^{\frac{R_n^l}{W_l}-1})\sigma^2}{R_n^l},$$

$$G_2 = \frac{(2^{\frac{R_{ni}^s}{W_l}-1})\sigma^2}{R_{ns}^s}.$$

Theorem 1. The proposed channel selection game is a potential game with the potential function Φ(a) in (12) satisfying,

$$\begin{aligned} &\Phi(a_n', a_{-n}) - \Phi(a_n, a_{-n}) \\ &= 2S_n' D_n^\alpha (U_n(a_n', a_{-n}) - U_n(a_n, a_{-n})). \end{aligned} \tag{13}$$

Proof. See appendix A.

A detailed proof of theorem 1 is given in appendices. As a result, we can get that the proposed channel selection game is a potential game with the potential function (12) and hence has a Nash equilibrium.

4 Algorithm Design

In this section, we design a distributed channel selection algorithm based on the property of a potential game.

4.1 Distributed Channel Selection Algorithm Design Principles

Next, we consider the problem that the MTs collectively determine the optimal channel selection profile such that the potential function is maximized, i.e.,

$$\underset{\mathbf{a}}{\mathrm{Max}} \quad \Phi(\mathbf{a}) \tag{14}$$

Problem (14) is a combinatorial optimization problem of finding the optimal channel selection profile over the discrete strategy space. Such a problem is very challenging, especially when the strategy space size is large.

We then consider approaching the potential maximization solution approximately. Then, we formulate problem (14) into the following equivalent problem:

$$\begin{aligned} &\underset{q_a \geq 0}{\mathrm{Max}} \quad \sum_a q_a \mathbf{\Phi}(\mathbf{a}) \\ &\text{s.t.} \quad \sum_{a \in \Theta} q_a = 1 \end{aligned} \tag{15}$$

where q_a is the probability that the channel selection profile $\mathbf{a}$ is adopted. Obviously, the optimal solution to problem (15) is to choose the optimal channel selection profiles with probability one. It is known from [34] that problem (15) can be approximated by the following convex optimization problem:

$$\begin{aligned} &\underset{q_a \geq 0}{\mathbf{Max}} \quad \sum_{\mathbf{a}} q_a \Phi(\mathbf{a}) - \frac{1}{\theta} \sum_{\mathbf{a}} q_a \ln q_a \\ &\textbf{s.t.} \quad \sum_{\mathbf{a}} q_a = 1 \end{aligned} \tag{16}$$

We see that, when $\theta \to \infty$, problem (16) becomes exactly the same as problem (15). Specifically, when $\theta \to \infty$, the optimal solutions that maximize the potential function Φ(a) will be selected with probability one. A nice property of such an approximation in (16) is that we can obtain a closed form solution, which facilitates the later distributed algorithm design.

Proposition 1. By using the KKT condition [32], we can derive the optimal solution to problem (15) as,

$$q_a^* = \frac{\exp(\theta\Phi(\mathbf{a}))}{\sum_{\hat{\mathbf{a}}}\exp(\theta\Phi(\hat{\mathbf{a}}))}. \quad \textbf{(17)}$$

Proof. See appendix B.

Next, we design a distributed channel selection algorithm, such that the dynamic channel selection of the MTs forms a Markov chain (with the system state is the channel selection profile $\mathbf{a}$). As long as the Markov chain converges to the stationary distribution as given in (17), we can approach the Nash equilibrium channel selection profile that maximizes the potential function by setting a sufficiently large parameter θ.

4.2 Channel Selection Markov Chain Design

According to (19), we have that

$$\begin{aligned}&\Phi(a_n', \mathbf{a}_{-n}) - 2S_n' D_n^\alpha U_n(a_n', \mathbf{a}_{-n}) \\ &= \Phi(a_n, \mathbf{a}_{-n}) - 2S_n' D_n^\alpha U_n(a_n, \mathbf{a}_{-n})\end{aligned} \quad \textbf{(18)}$$

Equation (18) implies that an increase (or decrease) of the potential function $\Phi(\mathbf{a})$ equals a weighted decrease (or increase) of each MT's utility. Based on this equation, we propose a distributed channel selection algorithm that only requires information exchange in each MT's current channel state.

As shown in Algorithm 1, the proposed algorithm works in a distributed manner such that when the MT transits to a new channel, it will measure its estimation utility $\hat{U}_n$ and update its channel selection according to a timer value that follows an exponential distribution with a rate of τ_n. Because the probability density function of the exponential distribution is continuous, the probability that more than one MT will generate the same timer value and update their channels simultaneously equals zero. As a result, one MT will perform the channel selection update at a time, and the direct transitions between two system states a_n' and a_n are feasible if these two system states differ by one and only one MTs channel selection.

Because MT n will randomly chosen a new channel a_n' and adhere to this channel with probability

$$\frac{\exp(-2\theta S_n' D_n^\alpha U_n(a_n, a_{-n}))}{\exp(-2\theta S_n D_n^\alpha U_n(a_n, a_{-n})) + \exp(-2\theta S_n D_n^\alpha U_n(a_n', a_{-n}))} \quad \textbf{(19)}$$

The probability of transition from state (a_n, a_{-n}) to (a_n', a_{-n}) is

$$\frac{1}{|\mathbf{M}|} \times \frac{\exp(-2\theta S_n' D_n^\alpha U_n(a_n, a_{-n}))}{\exp(-2\theta S_n D_n^\alpha U_n(a_n, a_{-n})) + \exp(-2\theta S_n D_n^\alpha U_n(a_n', a_{-n}))} \quad \textbf{(20)}$$

Because each MT n performs its channel selection update, according to the countdown timer mechanism with a rate of τ_n, the transition rate from state $\mathbf{a}$ to state $\mathbf{a}'$ is given as $q_{a,a'} = \frac{\tau_n}{|\mathbf{M}|} \times$

$$\frac{\exp(-2\theta S_n' D_n^\alpha U_n(a_n', a_{-n}))}{\exp(-2\theta S_n D_n^\alpha U_n(a_n, a_{-n})) + \exp(-2\theta S_n D_n^\alpha U_n(a_n', a_{-n}))} \quad \textbf{(21)}$$

otherwise, we have $q_{a,a'} = 0$.

The process of the algorithm is summarized in Algorithm 1. We then show in the following theorem that the channel selection Markov chain is time reversible, which means that the stochastic behavior of the reverse Markov chain remains the same when tracing the Markov chain backward. A nice property of a time reversible

Algorithm 1. Distributed Channel Selection Algorithm

Initialization:

1. Set the approximation parameter θ and the rate τ_n
2. Choose a channel a_n randomly for each MT n $\in$ N.

End Initialization

3. For each MT n $\in$ N in parallel:
4. **loop**
5. **Generate** a timer value following an exponential Distribution with mean equal to $\frac{1}{\tau_n}$.
6. **Count down** until the timer expires.
7. **if** the timer expires **then**
8. Measure the estimation energy consumption utility $\hat{U}_n(a_n, a_{-n})$ on the chosen channel an.
9. **choose** a new channel a_n' randomly.
10. **Measure** the estimated energy consumption utility $\hat{U}_n(a_n', a_{-n})$ on the new chosen channel a_n'
11. **Stay** in the new channel a_n' with probability
$$\frac{\exp(-2\theta S_n' D_n^\alpha \hat{U}_n(a_n, a_{-n}))}{\exp(-2\theta S_n' D_n^\alpha \hat{U}_n(a_n, a_{-n})) + \exp(-2\theta S_n' D_n^\alpha \hat{U}_n(a_n', a_{-n}))}$$
or switch back to the original channel a_n with probability
$$\frac{\exp(-2\theta S_n' D_n^\alpha \hat{U}_n(a_n', a_{-n}))}{\exp(-2\theta S_n' D_n^\alpha \hat{U}_n(a_n, a_{-n})) + \exp(-2\theta S_n' D_n^\alpha \hat{U}_n(a_n', a_{-n}))}$$
12. **end if**
13. **end loop**

Markov chain is that it always admits a unique stationary distribution, independent of the initial system state. This implies that, given any initial channel selection, the algorithm can drive the system to converge to the stationary distribution given in (17).

The system state of the channel selection Markov chain is defined as the channel selection profile a ∈ Θ of all MTs. Because it is possible to transfer from any state to another state in a finite number of transition steps, the spectrum access Markov chain is irreducible and has a stationary distribution. We show in the appendices that the Markov chain is time reversible by proving that the distribution in (17) satisfies the following detailed balance equation:

$$q_a^* \times q_{a,a'} = q_{a'}^* \times q_{a',a} \tag{22}$$

Theorem 2. The distributed channel selection algorithm induces a time-reversible Markov chain with the unique stationary distribution given in (17).

Proof. See appendix C.

Remark: According to steps 8-11 of Algorithm 1, MTs just needs to know the cooperative utility in the currently channel, then, select another channel with a certain probability. Thus, the MTs do not need to know the channel situation of all mobile devices. The algorithm makes the MTs that are close to each other select the same channel. According to Step 3 of the cooperative offloading, every MT in the same channel acts as the header in turn and works for a same time duration, this can be guaranteed by the MAC layer protocol. Thus, the algorithm is robust to the dynamic offloading tasks. Indeed, the Algorithm enable the MTs that are close to each other to work in the same channel and reach to a stable state finally. For the dynamic network, the algorithm will enable the MTs to search the MTs who are close to each other, but cannot, maintain a stable state. Thus, in practice, the MAC layer detection of the devices can exclude the highly mobile nodes from the cooperative offloading and the Algorithm.

4.3 Performance Analysis

According to Theorem 2, we can obtain the Nash equilibrium $\mathbf{a}^*$ that maximizes the potential function $\Phi(\mathbf{a})$ of the channel selection game by setting the parameter $\theta \to \infty$. However, in practice, we can only implement a finite value of θ. Let $\bar{\Phi} = \sum_{\mathbf{a}} \Phi(\mathbf{a})$ be the expected potential value obtained by Algorithm 1, and let $\Phi^* = \operatorname{Max}_{\mathbf{a}} \Phi(\mathbf{a})$ be the maximum potential value.

We then show in Theorem 3 that, when a sufficiently large θ is adopted, the performance gap between $\bar{\Phi}$ and Φ^* is very small. This implies that we can achieve the Nash equilibrium by setting a sufficiently large θ.

Theorem 3. For the channel selection game that we formulate, we have that

$$0 \le \Phi^* - \bar{\Phi} \le \ln|\Theta| \tag{23}$$

where |Θ| denotes the number of feasible channel selection profiles of all MTs.

Proof.

According to (15) and (16), and we can have that

$$\operatorname*{Max}_{q_a \ge 0} \sum_a q_a \mathbf{\Phi}(\mathbf{a}) \le \operatorname*{\mathbf{Max}}_{q_a \ge 0} \sum_{\mathbf{a}} q_a \Phi(\mathbf{a}) - \frac{1}{\theta} \sum_{\mathbf{a}} q_a \ln q_a . \tag{24}$$

This is because

$$0 \le -\frac{1}{\theta} \sum_{a \in \Theta} q_a \ln q_a \le -\frac{1}{\theta} \ln|\Theta| .$$

Since q_a^* is the optimal solution to (15) and $\Phi^* = \operatorname*{Max}_{q_a, \mathbf{a}} q_a \Phi(\mathbf{a})$, according to (24), we have that

$$\begin{aligned} \Phi^* &\le \sum_{a \in \Theta} q_a^* \Phi(\mathbf{a}) - \frac{1}{\theta} \sum_{a \in \Theta} q_a^* \ln q_1^* \\ &\le \sum_{a \in \Theta} q_a^* \Phi(\mathbf{a}) + \frac{1}{\theta} \ln|\Theta| \\ &\le \bar{\Phi} + \frac{1}{\theta} \ln|\Theta| \end{aligned} \tag{25}$$

which completes the proof.

We next discuss the efficiency achieved by the distributed channel selection algorithm when θ is sufficiently large (i.e., $\theta \to \infty$). Let $V(\mathbf{a})$ be the total energy consumption of all the MTs under a strategy profile a, i.e., $V(\mathbf{a}) = \sum_{n=1}^{N} U_n(\mathbf{a})$ We denote $\tilde{\mathbf{a}}$ as the centralized optimal profile that minimizes the energy consumption and $\mathbf{a}^*$ as the convergent Nash equilibrium by the distributed channel selection algorithm. Notice that the centralized optimization can be solved by maximizing $V(\mathbf{a})$. We then define the efficiency ratio of the Nash equilibrium under the centralized optimal solution as

$$\eta = \frac{V(\tilde{\mathbf{a}})}{V(\mathbf{a}^*)} = \frac{\sum_{n=1}^{N} U_n(\tilde{\mathbf{a}})}{\sum_{n=1}^{N} U_n(\mathbf{a}^*)} , \tag{26}$$

which is always not greater than 1. A larger η implies that the distributed algorithm is more efficient compared to the

centralized optimal solution.

5 Numerical Results

The performance evaluations of the proposed distributed channel selection algorithm are illustrated in this section. We first consider a wireless network with M = 4 channels in the BS and N = 10 cooperative MTs. As shown in Figure 3, these MTs are scattered across a square area of 250 m, which is a suitable distance for D2D communication. The offloading data size of each MT is set to 6, 1.5, 3, 1, 1, 2, 4, 1, 3, and 8 MB. We set $W_l = 5MHz$ and $R_n^l = 6\times10^6 bps$ for long links and $W_s = 1MHz$ and $R_{ni}^s = 2\times10^5 bps$ for short links. The white Gaussian noise power is -100 dBm.

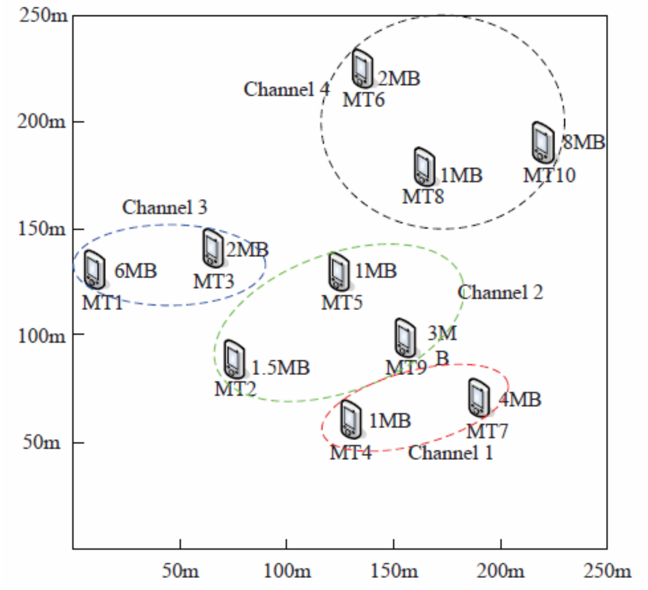


Figure 3. A square area with a length of 250 m with 10 scattered MTs

We show in Figure 4 that when the parameter θ is sufficiently large (we set $\theta = 10^6$ in the simulation), the algorithm can converge to the optimal potential function value Φ^*. It also verifies the existence of the Nash equilibrium of the distributed channel selection algorithm. The gap between the expected potential value and the optimal potential value becomes very small when the iteration goes to approximately 250 steps.

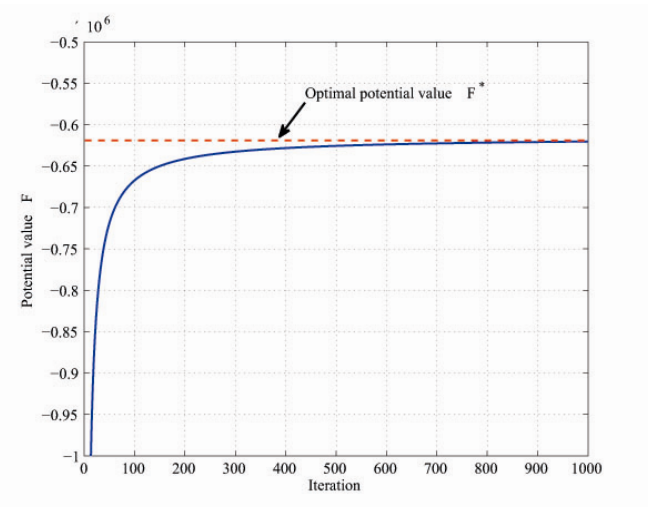


Figure 4. Convergence of potential value Φ when $\theta = 10^6$

Figure 5 demonstrates the convergence of the MT's energy consumption with increasing iterations. At the beginning, each MT chooses a channel randomly; thus, the energy consumption is high. As the iteration increases, MTs with the distributed algorithm gradually self organize into stable groups and form different cooperation clusters. As shown in figure 2, MTs that are close to each other tend to select the same channel to form a coalition. As shown in the Figure, more steps are required for convergence as the number of channels increases. However, the number of iterations will not increase significantly. For instance, the iteration increases from 180 to 395 when the number of channels increases from 3 to 8. Therefore, the number of iterations to convergence is acceptable, and the proposed distributed algorithm is efficient.

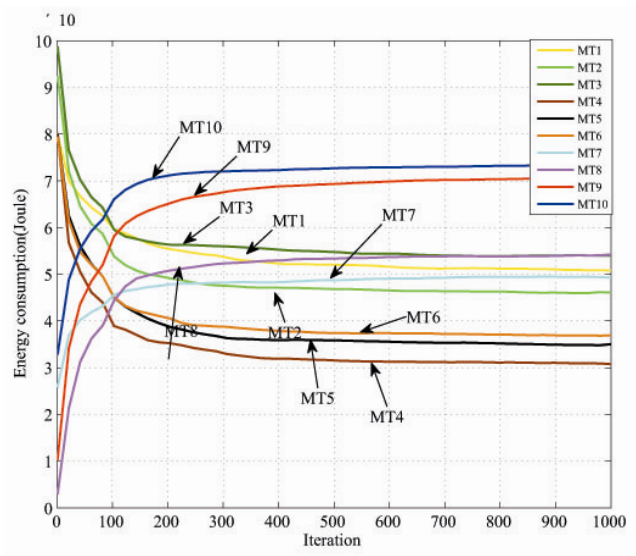


Figure 5. Energy consumption with iteration

To evaluate the performance of the proposed algorithm, we also compare the total energy consumption in this wireless network to a centralized optimization, which can be computed as $\mathbf{Min}_{\mathbf{a}} \sum_{n=1}^{N} E_n$.

We should notice that the centralized optimization solution requires complete network information such as the geo-locations, the transmission power and the set of feasible channels of all MTs. However, the proposed distributed channel selection algorithm only requires each MT to measure its own energy consumption based on its current channel.

Table 1 shows the iterations when the number of channels changes. As shown in the table, more steps are required for convergence as the number of channels increases. However, the number of iterations will not increase significantly. For instance, the iteration increases from 180 to 395 when the number of channels increases from 3 to 8. Therefore, the number of iterations to convergence is acceptable, and the proposed distributed algorithm is efficient.

We investigate the influence of the number of channels on energy consumption. Figure 6 shows that the energy consumption of MT4 decreases as the number of channels increases. We show in Figure 6 that, with an increase in channels, the MT can achieve lower energy consumption. For instance, MT4 sees a reduction of 5 Joules of energy consumption when the number of channels increases from 3 to 5. This is because, with increasing channel bandwidth, fewer MTs compete for bandwidth in one channel, and each MT can cooperate with closer MTs.

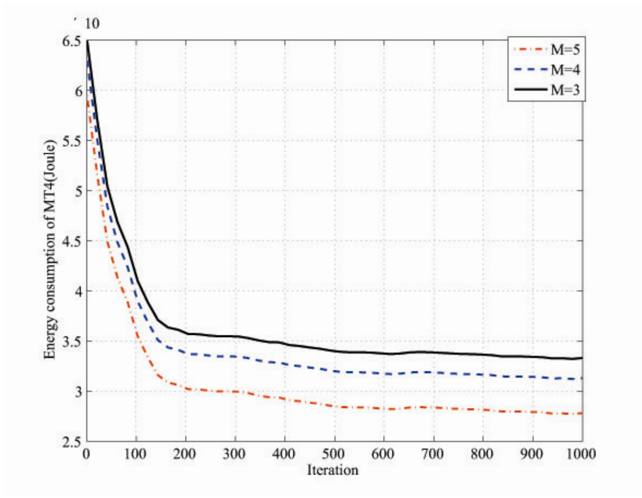


Figure 6. Energy consumption of MT4 with different number of channels

In Figure 7, the system's total energy consumption decreases when the number of channels increases. Moreover, the shrinking gap between the centralized algorithm and the distributed algorithm demonstrates the high efficiency of the proposed algorithm. When the number of channels increases to 7 or 8, the system's total energy consumption remains unchanged.

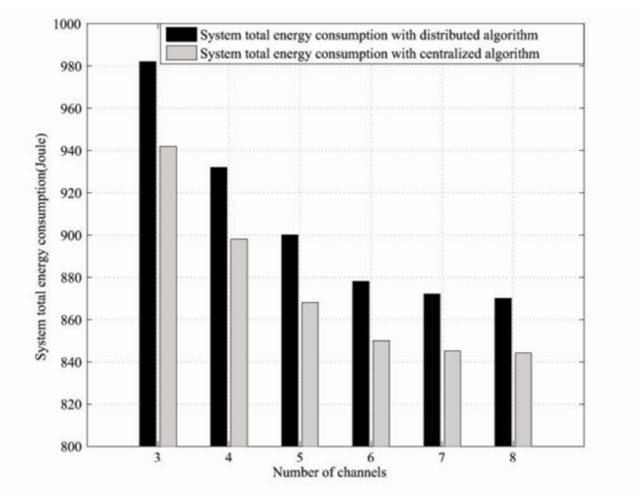


Figure 7. System's total energy consumption and iterations with different number of channels

In Figure 8, we analyze the performance by varying the number of MTs. It is clear that the system's total energy consumption increases with increasing number of MTs under all schemes. In addition, we observe that data offloading using cooperation can provide 55% energy savingscompared to offloading not using cooperation.

This is because the MTs can reduce unnecessary long-link transmissions using cooperation. Moreover, the proposed distributed algorithm achieves about the 85% energy efficiency, compared with the centralized optimization solution for all cases where the number of MTs varies from 10 to 50. With additional MTs in the network, the distributed algorithm can also achieve a good efficiency.

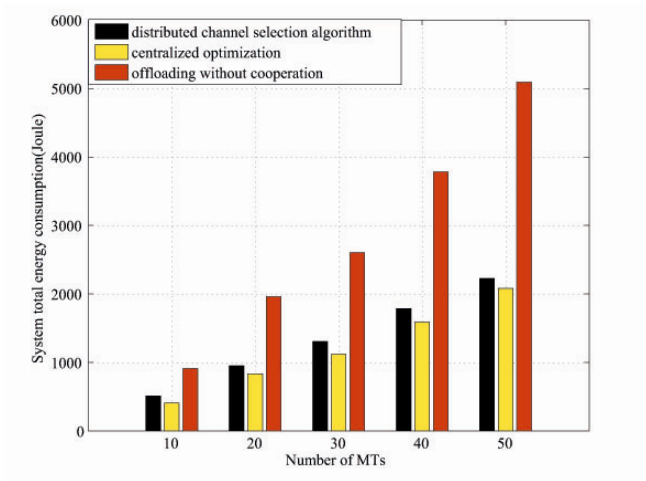


Figure 8. The comparison of the system total energy consumption between the distributed channel selection algorithm and the centralized optimization

Figure 9 presents the system's total energy consumption with different offloading data sizes in the system. Our scheme can be implemented periodically to enable MTs to perform collaborative offloading. We implement the experiment by simultaneously increasing all the MTs' offloading size such that the system's total offloading data size varies from 20 MB to 100 MB for a period. We consider here to use such small data, since the typical IOT data often has a small size. For example, the typical M2M data monthly plans can be 1MB, 5MB, 10MB to 1 Gb for the operators T-mobile, Vodafon or Verizon [40]. With increasing total data size, the performance gap between the distributed channel selection algorithm and the centralized optimization becomes increasingly smaller, and when the data size is 100 MB, the efficiency gap between the distributed algorithm and the centralized optimization can be reduced to less than 8%.

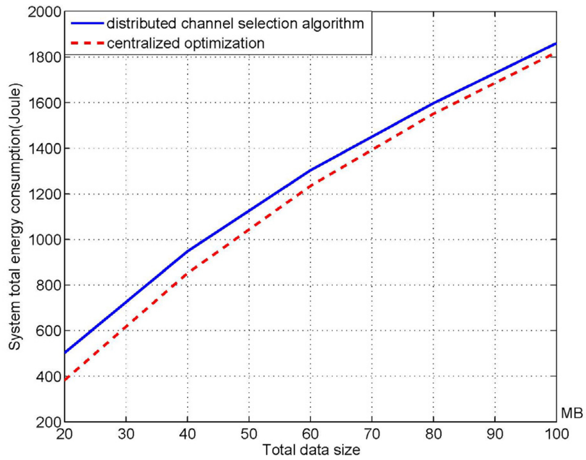


Figure 9. The system's total energy consumption with different offloading data sizes

Finally, we investigate the impact of the coverage of the network on the performance. We conduct experiments by varying the distance from 100 m×100 m to 250 m×250 m. As shown in Table 2, as the MTs become closer to each other, the energy consumption of the short links is reduced; therefore, the efficiency of the proposed algorithm is better than the 250m × 250m case. For example, the efficiency in the 250 m×250 m case is 87.4%; however, it increases to 92.1% when the experiment is implemented using 100 m×100 m. This shows that the proposed algorithm achieves a good efficiency in shorter range communication.

Table 2. Energy consumption comparison and efficiency

	Energy consumption (J) with distributed algorithm	Energy consumption (J) with centralized solution	Efficiency
100m	91.4	84.2	92.1%
150m	243.0	218.5	89.9%
200m	387.6	342.6	88.4%
250m	507.1	443.1	87.4%

6 Conclusion

In this paper, we proposed the distributed wireless channel selection scheme with peer-assisted data offloading in each channel. The proposed scheme enables mobile devices to help each other in proximity to perform the computing task and offload the data. And, the distributed channel selection problem among the MTs is formulated as a potential game which has been proved that has a unique Nash equilibrium. Using the Markov chain principle, a distributed channel selection algorithm was designed to achieve the Nash equilibrium. The results show that MTs form coalitions according to both their offloading data sizes and the distance to other peers. This means that an MT prefers to cooperate with users who are closer to him and have less data. Moreover, we have compared the energy efficiency ratio to the centralized optimal solution. Numerical results have demonstrated that the proposed distributed algorithm is efficient compared to the centralized solution.

Acknowledgements

This work was supported in part by the National Key R&D Program of China (2018YFC1314903), in part by the NSF of Jiangsu Province under Grant BK20161518, in part by the Open Research Fund of National Mobile Communications Research Laboratory, Southeast University, under Grant 2018D05, in part by the National Natural Science Foundation of China under Grant 61772287, in part by the Institute of Advance Technology Project, NJUPT, under Grant XJKY15008, and in part by the Open Research Fund of Jiangsu Engineering Research Center of Communication and Network Technology, NJUPT.

References

[1] E. Baccarelli, N. Cordeschi, A. Mei, M. Panella, Energy-efficient Dynamic Traffic Offloading and Reconfiguration of Networked Data Centers for Big Data Stream Mobile Computing: Review, Challenges, and a Case Study, *IEEE Network*, Vol. 30, No. 2, pp. 54-61, March, 2016.

[2] X. Wang, J. Wang, X. Wang, X. Chen, Energy and Delay Tradeoff for Application Offloading in Mobile Cloud Computing, *IEEE Systems Journal*, Vol. 11, No. 2, pp. 858-867, June, 2017.

[3] G.-H.-S. Carvalho, I. Woungang, A. Anpalagan, M. Jaseemuddin, E. Hossain, Intercloud and HetNet for Mobile Cloud Computing in 5G Systems: Design Issues, Challenges, and Optimization, *IEEE Network*, Vol. 31, No. 3, pp. 80-89, May/June, 2017.

[4] M. Altamimi, Riyadh, A. Abdrabou, K. Naik, A. Nayak, Energy Cost Models of Smartphones for Task Offloading to the Cloud, *IEEE Transactions on Emerging Topics in Computing*, Vol. 3, No. 3, pp. 384-398, January, 2015.

[5] Z.-F. Xiao, Y. Xiao, H. Chen, An Accountable Framework for Sensing-Oriented Mobile Cloud Computing, *Journal of Internet Technology*, Vol. 15, No. 5, pp. 813-822, September, 2014.

[6] H. Flores, Tartu, P. HuiSasu, Y. Li, Mobile Code Offloading: From Concept to Practice and Beyond, *IEEE Communications Magazine*, Vol. 53, No.3, March, 2015.

[7] H. Zhou, H. Wang, X. Li, V. C. M. Leung, A Survey on Mobile Data Offloading Technologies, *IEEE Access*, Vol. 6, pp. 5101-5111, January, 2018.

[8] K. Zheng, H.-L. Meng, L. Hou, K. Lin, L. Hu, Dynamic Offloading Schemes for Mobile Cloud Computing Services in Heterogeneous Networks, *Journal of Internet Technology*, Vol. 16, No. 2, pp. 335-342, March, 2015.

[9] J.-F. Wang, X.-B. Shi, D.-M. Xiao, P. Zhou, Y. Hu, Efficient Mobile Agent Based Data Dissemination by Distributed Offloading, *Journal of Internet Technology*, Vol. 18, No. 1, pp. 189-198, January, 2017.

[10] X. Chen, Q. Shi, L. Yang, J. Xu, ThriftyEdge: Resource-Efficient Edge Computing for Intelligent IoT Applications, *IEEE Network*, Vol. 32, No. 1, pp. 61-65, January-February, 2018.

[11] H. El-Sayed, S. Sankar, M. Prasad, D. Puthal, A. Gupta, M. Mohanty, C.-T. Lin, Edge of Things: The Big Picture on the Integration of Edge, IoT and the Cloud in a Distributed Computing Environment, *IEEE Access*, Vol. 6, pp. 1706-1717, December, 2017.

[12] A. Kiani, N. Ansari, Edge Computing Aware NOMA for 5G Networks, *IEEE Internet of Things Journal*, Vol. 5, No. 2, pp. 1299-1306, April, 2018.

[13] M. Hui, L. Wang, J.-X. Wang, T.-L. Hu, Y.-L. Tang, L.-F. Huang, Delay-Constraint Offloading and Joint Resource Allocation in MEC Based Vehicular Network, *Journal of Internet Technology*, Vol. 18, No. 7, pp. 1615-1625, December, 2017.

[14] D. Suh, H. Ko, S. Pack, Efficiency Analysis of WiFi Offloading Techniques, *IEEE Transactions on Vehicular Technology*, Vol. 65, No. 5, pp.3813-3817, May, 2015.

[15] Y. Im, C. Joe-Wong, S. Ha, S. Sen, AMUSE: Empowering Users for Cost-Aware Offloading with Throughput-Delay Tradeoffs, *IEEE Transactions on Mobile Computing*, Vol. 15, No. 5, pp. 1062-1076, July, 2015.

[16] K. Huguenin, E. L. Merrer, N. L. Scouarnec, G. Straub, Efficient and Transparent Wi-Fi Offloading for HTTP(S) POSTs, *IEEE Transactions on Mobile Computing*, Vol. 15, No. 4, pp.826-839, June, 2016.

[17] T. Lei, X. Wen, Z. Lu, X. Zhao, Y. Li, B. Zhang, SWN: An SDN Based Framework for Carrier Grade Wi-Fi Networks, *China Communications*, Vol. 13, No. 3, pp.12-26, April, 2016.

[18] K. Poularakis, G. Iosifidis, I. Pefkianakis, L. Tassiulas, Mobile Data Offloading through Caching in Residential 802.11 Wireless Networks, *IEEE Transactions on Network and Service Management*, Vol. 13, No. 1, pp. 71-84, January, 2016.

[19] M. Nir, A. Matrawy, M. St-Hilaire, An Energy Optimizing Scheduler for Mobile Cloud Computing Environments, *Proc.of IEEE INFOCOM*, Toronto, Canada, 2014, pp. 404 - 409.

[20] Y. Geng, W. Hu, Y. Yang, W. Gao, G. Cao, Energy-Efficient Computation Offloading in Cellular Networks, *IEEE 23rd International Conference on Network Protocols (ICNP)*, San Francisco, CA, USA, 2015, pp. 145-155.

[21] H.-H. Yang, J. Lee, T-.Q.-S. Quek, Heterogeneous Cellular Network with Energy Harvesting-based D2D Communication, *IEEE Transactions on Wireless Communications*, Vol. 15, No. 2, pp. 1406-1419, October, 2016.

[22] C.-S. You, K. Huang, H. Cha, Energy Efficient Mobile Cloud Computing Powered by Wireless Energy Transfer, *IEEE Journal on Selected Areas in Communications*, Vol. 34, No. 5, pp. 1757-1771, March, 2016.

[23] N. Cheng, N. Lu, N. Zhang, T. Yang, Vehicle-Assisted Device-to-Device Data Delivery for Smart Grid, *IEEE Transactions on Vehicular Technology*, Vol. 65, No. 4, pp. 2325-2340, March, 2016.

[24] X. Lyu, H. Tian, Adaptive Receding Horizon Offloading Strategy Under Dynamic Environment, *IEEE Communications Letters*, Vol. 20, No. 5, pp. 878 -881, February, 2016.

[25] Z. Zang, L. Song, Z. Han, W. Saad, Coalitional Games with Overlapping Coalitions for Interference Management in Small Cell Networks, *IEEE Transactions on Wireless Communications*, Vol. 13, No. 5, pp. 2659-2669, May, 2014.

[26] L.-A. Kanj, Z. Dawy, W. Saad, E. Kutanoglu, Energy-Aware Cooperative Content Distribution over Wireless Networks: Optimized and Distributed Approaches, *IEEE Transactions on Vehicular Technology*, Vol. 62, No. 8, pp. 3828-3847, October, 2013.

[27] Z. Chang, J. Skyla, T. Ristaniemi, Energy Efficient User Grouping and Scheduling for Collaborative Mobile Cloud, *in Proc. of IEEE ICC*, Sydney, NSW, Australia, 2014, pp. 4281-4286.

[28] Y. Wu, J. Chen, L. Qian, J. Huang, Energy-Aware Cooperative Traffic Offloading via Device-to-Device Cooperations: An Analytical Approach, *IEEE Transactions on Mobile Computing*, Vol. 16, No. 1, pp. 97-114, January, 2017.

[29] H. Debnath, G. Gezzi, A. Corradi, N. Gehani, X. Ding, R. Curtmola, C. Borcea, Collaborative Offloading for Distributed Mobile-Cloud Apps, *2018 6th IEEE International Conference on Mobile Cloud Computing, Services, and Engineering (MobileCloud)*, Bamberg, Germany, 2018, pp. 87-94.

[30] G. Chandrasekaran, N. Wang, M. Hassanpour, M. Xu, R. Tafazolli, Mobility as a Service (MaaS): A D2D-Based Information Centric Network Architecture for Edge-Controlled Content Distribution, *IEEE Wireless Communications*, Vol. 6, pp. 2110-2129, December, 2018.

[31] X. Wang, Y. Zhang, V.- C.- M. Leung, N. Guizani, T. Jiang, D2D Big Data: Content Deliveries over Wireless Device-to-Device Sharing in Large-Scale Mobile Networks, *IEEE Wireless Communications*, pp 32-38, February, 2018.

[32] C. Huang, M. Chiang, D. Dao, W. Su, S. Xu, H. Zhou, V2V Data Offloading for Cellular Network Based on the Software Defined Network (SDN) Inside Mobile Edge Computing (MEC) Architecture, *IEEE Access*, Vol. 6, pp. 17741-17743, March, 2018.

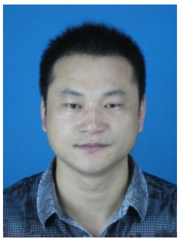
[33] Y. Geng, G. Cao, Peer-Assisted Computation Offloading in Wireless Networks, *IEEE Transactions on Wireless Communications*, Vol. 17, No. 7, pp. 4565-4578, April, 2018.

[34] G. Iosifidis, L. Gao, J. Huang, L. Tassiulas, A Double-auction Mechanism for Mobile Data-offloading Markets, *IEEE/ACM Transactions on Networking*, Vol. 23, No. 5, pp. 1634-1647, October, 2015.

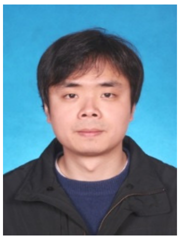
[35] V. Cardellini, V. De Nitto Personé, V. Di Valerio, F. Facchinei, V. Grassi, F. Lo Presti, V. Piccialli, A Game-theoretic Approach to Computation Offloading in Mobile Cloud Computing, *Mathematical Programming: Series A and B*, Vol. 157, pp. 421-449, June, 2016.

[36] X. Chen, L. Jiao, W. Li, X. Fu, Efficient Multi-User Computation Offloading for Mobile-Edge Cloud Computing, *IEEE/ACM Transactions on Networking*, Vol. 24, No. 5, pp. 2795-2808, October, 2016.
[37] X. Ma, C. Lin, X. Xiang, C. Chen. Game-theoretic Analysis of Computation Offloading for Cloudlet-based Mobile Cloud Computing, *Proceedings of the 18th ACM International Conference on Modeling, Analysis and Simulation of Wireless and Mobile Systems (MSWiM' 15)*, New York, NY, USA, pp. 271-278.
[38] Z. Jiang, B. Huang, D. Li, The Join Collaborative Data Offloading and Distributed Channel Selection in Wireless Networks, *Proc. of IEEE WCSP 2016*, Yangzhou, China, 2016, pp. 1-5.
[39] D. Monderer, L. S. Shapley, Potential Games, *Games and Economic Behavior*, Vol. 14, pp. 124-143, May, 1996.
[40] Cellular Data Plans for M2M Applications, http://www.embeddedworks.net/m2m-data.html.

Biographies



Yongan Guo received the M.S. and Ph.D. (Hons.) degrees in signal and information processing from the Nanjing University of Postsand Telecommunications, Nanjing, China, in 2012 and 2018, respectively. He is currently an Associate Professor with the Nanjing University of Posts and Telecommunications. His current research interests include wireless multimedia modeling, capacity prediction, and wireless network coding.



Dapeng Li received the B.S. degree in electronics and the M.S. degree in communication systems from Harbin Engineering University, Harbin, China, in 2003 and 2006, respectively, and the Ph.D. degree from the Department of Electronic Engineering, Shanghai Jiao Tong University, Shanghai, China, in 2010. From October 2007 to August 2008, he was working on 4G/LTE development at the R&D Center, Huawei Company, Shanghai, China. Currently, he is an Associate Professor at Nanjing University of Posts and Telecommunications, Nanjing, China. His research interests include future cellular networks, machine to machine communications, green networks, cognitive radio networks, radio resource management, and cooperative communications.

Ze Jiang received the M.E. degree from Nanjing University of Posts and Telecommunications, Nanjing, China, in 2017. He currently works at Baidu Company, China. His current research interests include cloud computing and edge computing.

Feng Tian received the Ph.D. degree in signal and information processing from the Nanjing University of Posts and Telecommunications, Nanjing, China, in 2008. He was a Visiting Scholar with the Virginia Polytechnic Institute and State University, Blacksburg, VA, USA, from 2013 to 2015. He is currently an Associate Professor with the Nanjing University of Posts and Telecommunications. His current research interests include performance optimization and algorithm design for wireless networks.

Appendices

A. Proof of Theorem 1

Proof. Suppose that MT n unilaterally changes its strategy a_n to a'_n n such that the strategy profile changes from $\mathbf{a}$ to $\mathbf{a}'$. We have that

$$\begin{aligned}
&\Phi(a'_n, a_{-n}) - \Phi(a_n, a_{-n}) \\
&= -G_1 D_n^{2\alpha}(\sum_{i\neq n} S_i S'_n \cdot I\{a_i, a'_n\} + \sum_{j\neq n} S'_n S_j \cdot I\{a'_n, a_j\}) \\
&-G_2 S_n'^2 D_n{}^{\alpha}(\sum_{i\neq n} d_{in}{}^{\alpha} \cdot I\{a_i, a'_n\} + \sum_{j\neq n} d_{nj}^{\alpha} \cdot I\{a'_n, a_j\}) \\
&-(-G_1 D_n^{2\alpha}(\sum_{i\neq n} S_i S'_n \cdot I\{a_i, a_n\} + \sum_{j\neq n} S'_n S_j \cdot I\{a_n, a_j\}) \\
&-G_2 S_n'^2 D_n^{\alpha}(\sum_{i\neq n} d_{in}{}^{\alpha} \cdot I\{a_i, a_n\} + \sum_{j\neq n} d_{nj}{}^{\alpha} \cdot I\{a_n, a_j\})) \\
&= -2S'_n D_n^{\alpha}(\sum_{i\neq n} G_1 D_n{}^{\alpha} S_i \cdot I\{a_i, a'_n\}) \\
&-\sum_{i\neq n} G_1 D_n^{\alpha} S_i \cdot I\{a_i, a'_n\}) \\
&-2S'_n D_n^{\alpha}(\sum_{i\neq n} G_2 S'_n d_{in}^{\alpha} \cdot \{a_i, a'_n\} \\
&-\sum_{i\neq n} G_2 S'_n d_{in}^{\alpha} \cdot I\{a_i, a_n\})
\end{aligned} \tag{27}$$

While

$$\begin{aligned}
&U_n(a'_n, a_{-n}) - U_n(a_n, a_{-n}) \\
&= -(\sum_{i} G_1 D_n^{\alpha} S_i \cdot I\{a_i, a'_n\} + \sum_{i\neq n} G_2 S'_n d_{in}^{\alpha} \cdot I\{a_i, a'_n\}) \\
&+(\sum_{i} G_1 D_n^{\alpha} S_i \cdot I\{a_i, a_n\} + \sum_{i\neq n} G_2 S'_n d_{in}^{\alpha} \cdot I\{a_i, a_n\}) \\
&= -(\sum_{i\neq n} G_1 D_n^{\alpha} S_i \cdot I\{a_i, a'_n\} + \sum_{i\neq n} G_2 S'_n d_{in}^{\alpha} \cdot I\{a_i, a'_n\}) \\
&+(\sum_{i\neq n} G_1 D_n{}^{\alpha} S_i \cdot I\{a_i, a_n\} + \sum_{i\neq n} G_2 S'_n d_{in}^{\alpha} \cdot I\{a_i, a_n\})
\end{aligned} \tag{28}$$

so we can obtain that

$$\begin{aligned}
&\Phi(a'_{\text{n}}, a_{\text{-n}}) - \Phi(a_{\text{n}}, a_{\text{-n}}) \\
&= 2S'_{\text{n}} D_n^{\alpha}(U_n(a'_n, a_{-n}) - U_n(a_n, a_{-n}))
\end{aligned} \tag{29}$$

which completes the proof.

B. Proof of Proposition 1

Proof. According to the KKT condition (22) and Lagrange Multipliers, we can obtain

$$\begin{aligned}
\frac{\partial L(q_a, \lambda)}{\partial q_a} &= \nabla\ (F(x) - \lambda(\sum_{a} q_a - 1)) \\
&= \frac{1}{\theta}(\ln q_a + 1) + \lambda - \Phi(a) = 0
\end{aligned} \tag{30}$$

and

$$\lambda(\sum_{a\in\Theta} q_a - 1) = 0 \tag{31}$$

From (32), we can obtain

$$q_a = \exp(\theta(\Phi(\mathbf{a}) + \lambda) - 1), \tag{32}$$

Applying (34) to (32), we have

$$\sum_{\mathbf{a}\in\Theta} \exp\Phi(\mathbf{a}) = \exp(1 - \lambda\theta) \tag{33}$$

Applying (35) to (33), we finally obtain (17).

C. Proof of Theorem 2

Proof. Define $\Delta_{\mathbf{a}}$ as the set of the feasible state space of $\mathbf{a}$

To obtain (22), we consider the following two cases:

(1) If $a' \notin \Delta_{\mathbf{a}}$ we have $q_{a,a'} = q_{a',a}$, and equation (26) holds.

(2) If $a' \in \Delta_{\mathbf{a}}$, according to (17) and (21), we have

$$\begin{aligned}
&q_a^* \times q_{a,a'} \\
&= \frac{\tau_n}{|\mathbf{M}|} \frac{\exp(\theta\Phi(a))}{\sum_{a\in\Theta} \exp(\theta\Phi(\hat{a}))} \\
&\times \frac{\exp(-2\theta S'_n D_n^{\alpha} U_n(a))}{\exp(-2\theta S'_n D_n^{\alpha} U_n(a)) + \exp(-2\theta S'_n D_n^{\alpha} U_n(a'))} \\
&= \frac{\tau_n}{|\mathbf{M}|} \frac{\theta(\Phi(a) - 2S'_n D_n^{\alpha} U_n(a)}{\sum_{a\in\Theta} \exp(\theta\Phi(\hat{a}))} \\
&\times \frac{1}{\exp(-2\theta S'_n D_n^{\alpha} U_n(a)) + \exp(-2\theta S'_n D_n^{\alpha} U_n(a'))}
\end{aligned} \tag{34}$$

and similarly,

$$\begin{aligned}
&q_a^* \times q_{a,a'} \\
&= \frac{\tau_n}{|\mathbf{M}|} \frac{\exp(\theta(\Phi(a') - 2S'_n D_n^{\alpha} U_n(a')))}{\sum_{a\in\Theta} \exp(\theta\Phi(\hat{a}))} \\
&\times \frac{1}{\exp(-2\theta S'_n D_n^{\alpha} U_n(a)) + \exp(-2\theta S'_n D_n^{\alpha} U_n(a'))}
\end{aligned} \tag{35}$$

As a result, we finally obtain (22). The channel selection Markov chain is hence time-reversible and has the unique stationary distribution, as given in (17).