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Game Theory-Based Smart Mobile-Data Offloading Scheme in 5G Cellular Networks

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Abstract: Mobile-data traffic exponentially increases day by day due to the rapid development of smart devices and mobile internet services. Thus, the cellular network suffers from various problems, like traffic congestion and load imbalance, which might decrease end-user quality of service. This work compensates for the problem of offloading in the cellular network by forming device-to-device (D2D) links. A game scenario is formulated where D2D-link pairs compete for network resources. In a D2D-link pair, the data of a user equipment (UE) is offloaded to another UE with an offload coefficient, i.e., the proportion of requested data that can be delivered via D2D links. Each link acts as a player in a cooperative game, with the optimal solution for the game found using the Nash bargaining solution (NBS). The proposed solution aims to present a strategy to control different parameters of the UE, including harvested energy which is stored in a rechargeable battery with a finite capacity and the offload coefficients of the D2D-link pairs, to optimize the performance of the network in terms of throughput and energy efficiency (EE) while considering fairness among links in the network. Simulation results show that the proposed game scheme can effectively offload mobile data, achieve better EE and improve the throughput while maintaining high fairness, compared to an offloading scheme based on a maximized fairness index (MFI) and to a no-offload scheme.

Keywords: cellular network; cellular offloading; device-to-device; cooperative game; fairness index; Nash bargaining solution; energy consumption.

1. Introduction

Over the past few decades, the demands on wireless cellular networks (WCNs) have been increasing fast, with applications on UEs which are mobile devices used directly by end-users to communicate such as smart phones, tablets, and other new UEs. Mobile users in the networks rely more heavily to connect, interact, follow social media, watch live TV, and download music, etc. Moreover, according to a study by Cisco Systems, Inc. [1], global mobile-data traffic (MDT) has been growing explosively, and was expected to increase 7-fold between 2017 and 2022, reaching 77.5 exabytes per month by 2022. The ever-increasing MDT is one of the reasons end-user experience decreasing quality of service (QoS), and it creates challenges for cellular network operators (CNOs). To face this explosive traffic demand, CNOs need to upgrade their networks by either migrating to new-generation WCNs or developing enhancement techniques to significantly increase their network capacity. However, traditional methods, such as acquiring more licensed spectrum, developing new small-size cells, and upgrading technologies (e.g., from wide band code division multiple access [WCDMA] to Long Term Evolution [LTE]/LTE-Advanced [LTE-A]) are costly, time-consuming, and may not catch up to the pace of the traffic increase [2]. Clearly, CNOs must find novel methods to solve this problem, and mobile data offloading (MDO) appears to be one of the promising solutions that use complementary technologies (such as small cells and Wi-Fi networks) for delivering the

MDT originally targeted at cellular networks. MDO helps the network to increase overall throughput, reduces content delivery time, extends network coverage, increases network availability, and provides better EE. The performance benefits of MDO through small cells and Wi-Fi networks have been proven in the literature [3–9].

However, due to the limitations of backhaul connection and cross- or co-tier interference issues in the small-cell network, as well as service coverage and mobility in Wi-Fi networks, MDO through these networks is costly and impractical. A promising solution that has been considered lately for offloading MDT is opportunistic communications [10], and D2D communications can also be used to facilitate opportunistic communications [11,12]. D2D communications (also considered opportunistic) allows UEs in proximity to each other to exchange data directly without relying on infrastructure, and consequently, incurs very little or no monetary cost.

Extensive MDT has led researchers and designers to begin developing fifth-generation (5G) networks [13–15]. The authors in [13] mention challenges and current trends toward converged the fifth-generation (5G) mobile networks. The 5G networks are expected to have higher capacity and throughput when compared with the Fourth Generation (4G). However, the systems of 5G networks will need to face some new technical challenges, like Machine to Machine (M2M) communication, energy efficiency, complete ubiquity, autonomous management and increasing mobile traffic demands. Al-Falahy et al. [14] consider key five technologies that have the largest impact on progressing 5G: dense small-cell deployment, massive multiple-input multiple-output (M-MIMO), D2D, M2M, and millimeter-wave communications. Among the new features heralded by 5G, D2D communications could have a prominent role with systems or applications requiring low latency, and network traffic offloading. Moreover, computation offloading enabled by cloud/edge communication architecture can offload computation-excessive and latency-stringent applications to nearby devices through D2D communications or to nearby edge nodes through cellular or other wireless technologies [16,17]. Therefore, from the benefits of D2D communication in 5G cellular networks, MDO through D2D communication and offloading is a promising solution in reducing network load as demand for mobile traffic is increasing.

In recent works, wireless communications powered by external harvested energy has become a promising technique to deal with the energy-constraint problem. As a normal wireless node, a wireless device has a finite-capacity battery that can be recharged from ambient radio frequency (RF) signals and used for operations such as data processing and data transmission. The battery of a wireless device will store harvested energy without manually changing or recharging it. Recently, rectifying antenna design has become more efficient at harvesting energy from RF signals [18,19]. The RF signal comes from various sources such as wireless internet, radio stations, satellite stations, and digital multimedia broadcasting. Although the RF signal is abundant in space and can be retrieved without limit, there are still many unresolved problems of RF energy harvesting (RF-EH) in practical. One of practical issue related to RF-EH is hardware design for RF energy harvesters such as antenna with a large aperture, impedance matching circuit, rectifier, and voltage multiplier [20,21]. In addition to collecting energy from the ambient RF, the RF-EH device can also actively request energy from associated base stations and access points in some applications. In this case, the influence of the data flow and the energy flow on communication process is complicated due to interference of the energy transmission with the information decoding or interruption of the energy reception in the information transmission process [22]. Along with RF-EH, non-RF energy resources (solar, wind, etc.) can provide perpetual energy and higher power density for rechargeable batteries of wireless users [23,24]. Therefore, in this paper, we consider non-RF energy harvesting (NRF-EH) as one of the mobile-user controlled parameters that affect network performance.

In this paper, we study the problem of MDO via D2D links. Specifically, we consider an offloading scenario where one UE offloads its cellular traffic to another UE. Figure 1 provides an example of offloading in cellular networks where the hexagon denotes the coverage area of the CNO's macrocell and the interference among UEs is considered in the transmission process. In the data offload case,

data transmission between UEs can be made as follows: First, the source UE can offload some traffic to destination UE with an offload coefficient if D2D link is available, which is denoted as "the solid arrow" in the Figure 1. After that, the remaining data traffic of source UE will be transferred to the destination UE via BS, which is denoted as "dashed arrow". On the other hand, in the no-offload case, the data of source UE can be transmitted to destination UE only through BS-based transmission, and the offload coefficient will be zero. In Figure 1, UE1, UE2, and UE4 are source UE while UE3, UE5, and UE6 are destination UE. Even though Figure 1 shows 6 UEs case as an example. However, without loss of generality, the system model can be applied to 5G cellular networks. In such an offloading model, we are interested in the following issues: 1) How to offload data efficiently in terms of maximizing throughput and EE, and 2) How to equalize the offloading benefits among D2D links in the network. To do this, in the paper, we model and analyze the data offloading problem by using the NBS and Jain's fairness index. The main contributions of this paper are summarized as follows:

- We consider the problem of MDO in NRF-EH environments, where UEs can simultaneously harvest non-RF energy from the ambient environment (e.g., solar power) and execute data communications with other UEs via the path-loss model with a log normal distribution of shadow fading.
- We evaluate the performance of the schemes via MATLAB simulation under various network in terms of the fairness, throughput, and EE. In particular, a fairness based on Jain fairness index [25] is considered. For performance comparison, we consider two baseline scheme; the scheme where offload is not used and named "no-offload scheme", and the scheme where offload is used and fairness index (FI) is maximized, and named "MFI scheme". The numerical results provide valuable insight into the effect of the network parameters on the performance of the network.

Figure 1. A simple offloading example.

The rest of the paper is organized as follows. In Section 2, we present the related work and background. The NRF-EH model, the MDO model, and basic assumptions are described in Section 3. The NBS and the game model for MDO are presented in Section 4. The simulation results and discussions are provided in Section 5. Finally, Section 6 provides a conclusion.

2. Related Work and Background

Recently, there has been some work on MDO in WCNs, which roughly falls into three technologies [26]: for data traffic through small cells, on Wi-Fi networks and via opportunistic communications. In the following, we summarize the related work in each technology.

MDO through small cells is an effective method to reduce traffic congestion and network energy consumption in a heterogeneous cellular network (HCN) [26,27]. Chen et al. [26] provided a brief survey on existing traffic offloading techniques in WCNs, and they modeled the energy-aware traffic offloading problem in such HCNs as a discrete-time Markov decision process that puts forward an online reinforcement learning framework. Wang et al. [27] proposed an auction-based traffic offloading scheme to achieve both load balance among base stations (BSs) and fairness among UEs. Unfortunately, dense deployment of BSs in small cells is limited due to expensive backhaul connections and possible severe interference. Moreover, the problem of macrocell traffic admitted by incentivizing femtocell owners is recently studied [28–32]. The economic incentive issue is studied in MDO via third-party access points by using either the auction framework [33] or the non-cooperative Stackelberg game framework [34]. In general, these works studied the incentive issues using a non-cooperative game framework, which cannot capture the potential of coordination among players (which calls for a cooperative game approach). Lin et al. [35] studied the economic incentive issue by using a cooperative game framework (Nash bargaining) with the bargaining model between one mobile operator and one fixed-line operator, while the multi-player bargaining model in our work is a more general type of bargaining among D2D links. Liu et al. [36] applied the NBS for a fair user-association scheme in heterogeneous networks (HetNets), where different BSs are modeled as players to compete for serving users.

MDO on Wi-Fi networks provides a performance benefit that has been proven in the literature [3–8], and several works addressed the network economics of traffic offloading using game theory [2,37,38]. Gao et al. [2] modeled and analyzed MDO via third-party Wi-Fi and femtocell access points (APs) and proposed a one-to-many bargaining framework to study the economic incentive issues. In [37], Lee et al., modeled a market based on a two-stage sequential game, and investigated how much economic benefit can be generated from delayed Wi-Fi offloading. Paris et al. [38] formulated the problem of MDO as a reverse auction to offload the maximum amount of data traffic with the cheapest APs selected from the cellular network. However, service coverage and mobility are limited in Wi-Fi offloading, and CNOs usually find it impossible to capture complete visibility of traffic flows if using this offload technique for traffic offloading [26].

MDO via opportunistic communications exploits D2D communications as an overlay to offload traffic from the BSs [26]. With D2D communications, UEs in proximity to each other can exchange data directly without relying on a network infrastructure [39,40], and consequently, they get higher data rates and reduced power consumption [39–42]. Al-Kanj et al. [43] investigated the problem of traffic offloading in cellular networks by reducing the required number of long-distance channels while distributing common content to a group of UEs. Feng et al. [44] studied a resource allocation problem to maximize overall network throughput while guaranteeing QoS requirements for both D2D users and regular cellular users. Non-cooperative game model is employed to obtain a distributed resource allocation for D2D communications underlay cellular network [45–49]. Yin et al. [45] proposed a pricing-based interference coordination scheme using a pure non-cooperative game to mitigate the interference from D2D pairs to cellular users through setting a price by BS. The authors [46] modeled the competition among D2D pairs using non-cooperative power control game and proposed a distributed update rule to reach the Nash equilibrium with the interference from D2D transmissions to cellular users is coordinate using a pricing scheme. Chen et al. [47] studied a non-cooperative game model-based energy efficient resource allocation for D2D communication underlaying cellular networks in which each UE decide their respective transmission power over available resource blocks (RBs) with the goal of maximizing the achievable rate per unit power. Dominic [48] investigated the joint channel and power allocation for a D2D network by a distributed algorithm which converges to an action profile that maximizes the sum of players' utilities instead of a sub-optimal NE. Antonopoulos et al. [49] investigated MAC issues in D2D communication scenarios for wireless content dissemination and propose two energy-aware game theoretic MAC strategies (distributed and coordinated) where players decide if they transmit or not in each slot that estimate the NE transmission

probabilities in networks with multiple sources. In works on non-cooperative game model, each player acts selfishly to maximize its own payoff or utility function which based on the concept of a Nash equilibrium (no single agent can gain by unilaterally deviating) is not a very strong solution concept if a group of agents is able to gain by jointly changing their strategies. Moreover, in many instances of insufficient information of accurately model or the available formal procedures for the players during the strategic bargaining process; or the high complex model to offer a practical tool in the real world. In such cases, a cooperative game model allows analysis of the game easier with a simplified approach.

Recently, many interests are growing from various research communicates on RF-EH both in wireless sensor networks (WSNs) [50] and in D2D communication network [51,52]. Mekikis et al. [50] studied the impact of wireless energy harvesting (EH) to exchange successfully messages of nodes locally with their neighbors in large-scale dense network and proposed two scenarios: directly (direct communication (DC) scenario) or through a relay node (cooperative communication (CC) scenario). Although the two scenarios highlighted the importance of WEH in large-scale networks and the CC scenario is more advisable in applications with longevity matters, since it is superior in terms of lifetime. However, in randomly deployed dense networks, communication performance of the DC scenario is better than the CC scenario. In order to solve the EE resource allocation problem in the downlink EH-based D2D communication heterogeneous networks, a joint the EH time slot allocation, power and resource block allocation iterative algorithm based on the Dinkelbach and Lagrangian constrained optimization is proposed in [51]. In this study, a mixed-integer nonlinear constraints optimization problem is formulated, and the goal is to maximize the average EE. Sakr et al. [52] proposed two different spectrum access policies for the cellular network, namely random and prioritized access policies for cognitive D2D communication using RF-EH from the ambient interference in a multi-channel downlink-uplink cellular network. For evaluation of network performance, transmission probability and SINR outage probabilities for D2D and cellular users are considered under stochastic geometry. Although both [51,52] effectively address the issue of EE as well as transmission probability, the potential of coordination between D2D communications as well as network fairness has not been considered. In general, these existing works can neither capture the potential of coordination among D2D communications nor take fairness in payoff or NRF-EH into consideration under various network conditions in order to achieve the benefits and efficiencies of MDO.

Nash [53] established a basic two-person bargaining framework between two rational players, and proposed an axiomatic solution concept—NBS—which is characterized by a set of predefined axioms, and does not rely on a detailed bargaining process of the players. Since Nash's pioneering work, researchers have extended the bargaining analysis to cases with more than two players. In the multi-player scenario, some players may form groups and bargain jointly to improve their payoffs [54–56].

The NBS is a type of cooperative game that has been used for solving resource allocation problems among competing players. Nash proposed four axioms that should be satisfied by a reasonable bargaining solution [53]: Pareto efficiency, symmetry, invariance to affine transformations, and independence of irrelevant alternatives. The bargaining problem can be described as follows [54]. There are I players competing for a resource. Each player, i ($i \in \{1, 2, \dots, I\}$), requires a minimal payoff $U_i^{\min}$; let $\mathbf{U}^{\min} = (U_1^{\min}, \dots, U_i^{\min}, \dots, U_I^{\min})$ denote a set of the minimal payoffs for player $i \in \{1, 2, \dots, I\}$ over the reservation payoff or disagreement point of player i . Defining $\mathbf{U} = (U_1, \dots, U_i, \dots, U_I)$, $\mathbf{U}$ is a closed and convex set of payoffs over all possible agreements in order to present the set of feasible payoff allocations that the players can get when they cooperate. Since the minimal payoff of each player must be guaranteed, $\{U_i \in \mathbf{U} | U_i \geq U_i^{\min}, \forall i \in \{1, 2, \dots, I\}\}$ is a nonempty set. The NBS can be represented in a very simple form: it corresponds to an outcome that maximizes the product of both players' payoff gains upon a disagreement outcome.

Definition 1 (Nash bargaining solution [53,54]). *a set of payoffs $\mathbf{U} = (U_1, \dots, U_i, \dots, U_I)$, is an NBS (i.e., satisfying Nash's four axioms) if it solves the following problem:*

$$\mathbf{U}^* = \arg \max_{\mathbf{U}} \prod_{i=1}^I (U_i - U_i^{\min}) \quad (1)$$

$$\text{s.t. } U_i \geq U_i^{\min} \quad (2)$$

According to [56], if U_i is a concave upper-bounded function that has convex support, there exists a unique and optimal NBS.

3. System Model

In this section, we first consider the NRF-EH model for UEs which follows a stochastic Poisson process. Then, we model MDO with an offload coefficient in the transmission process.

3.1. NRF-EH Model

The performance of an autonomous energy harvesting communication node (EHCN) is considered to be a function of the random flow of harvested energy using an “energy packet” model which discretizes both the data flow and the energy flow in the sensor node based on queuing networks [57]. The arrival of energy and data packets to the nodes are both random processes: energy flows in at random through energy harvesting and data accumulates into the node, also at random, through sensing. Just as data packets are assumed to be collected into the EHCN in terms of discrete data packets, we consider that the harvested energy is also collect into the device's storage battery in discrete units of the energy packets [58–60]. Therefore, in this paper, an energy packet is defined as the minimum amount of energy needed to transmit a single data packet.

We assume that UEs always harvest non-RF energy (e.g., solar, wind, thermal) from the environment over the whole time slot in which each UE is powered by a limited-capacity battery and each battery is recharged by an energy harvester. Each UE can update the remaining energy in its battery at the end of every time slot for using in the next time slots. We consider practical case where arrived packets of harvested energy, denoted as $e^{hv}(t)$ energy packets in which $e^{hv}(t)$ take its value from ζ , are a finite number of energy packets. The value that $e^{hv}(t)$ has in time slot t can be described as follows:

$$e^{hv}(t) \in \{e_1^{hv}, e_2^{hv}, \dots, e_{\zeta}^{hv}\} \quad (3)$$

where $0 \leq e_1^{hv} < e_2^{hv} < \dots < e_{\zeta}^{hv} \leq E_{bat}$, in which the energy of the UE is stored in a battery with a finite capacity of E_{bat} energy packets.

We assume that the probabilities of harvested energy packets are followed a discrete probability distribution, as shown in (4):

$$Pr^{hv}(k) = \Pr[e^{hv}(t) = e_k^{hv}], k = 1, 2, \dots, \zeta \quad (4)$$

The harvested energy is assumed to follow a stochastic Poisson process. Subsequently, $e^{hv}(t)$ is a Poisson random variable with a mean value for harvested energy e_{mean}^{hv} . The probabilities in (4) can be rewritten as follows:

$$Pr^{hv}(k) \approx \frac{e^{-e_{mean}^{hv}} (e_{mean}^{hv})^k}{k!}, k = 1, 2, \dots, \zeta \quad (5)$$

3.2. Mobile-Data Offloading Model

We consider one CNO operating one macrocell with one BS and M UEs, in which each UE is equipped with a NRF-EH circuit that can harvest non-RF energy, denoted as UE_m , $m \in \mathcal{M}$, $\mathcal{M} =$

$\{1, 2, \dots, M\}$, and where UEs can offload cellular traffic to other UEs. Figure 2 show the MDO system model. The CNO serves a set of UEs that are randomly distributed geographically. In this paper, we study the problem of MDO via D2D links. Therefore, we consider D2D links that are available in the network. We assume that D2D links are independent, i.e., UEs that are either the source or destination in one D2D link is not the source or destination UE in another D2D link. For example, we have two D2D links (UE_m - UE_n and $UE_{m'}$ - $UE_{n'}$) as shown in Figure 2. Moreover, other UE activities such as transmitting from UE to BS (e.g., UE_1 -BS link) or idle (e.g., UE_M) will not affect directly to system performance that only interferes to other connections (e.g., UE_1 -BS links interfere to UE_m - UE_n and $UE_{m'}$ - $UE_{n'}$ links).

Figure 2. The MDO system model.

The traffic generated by a UE can be offloaded to another UE if the following conditions are all satisfied [2]:

- i. UEs are located within the same coverage area.
- ii. UEs are equipped with the same radio frequency interface and wireless communication protocol.
- iii. UEs are enabled to offload traffic.

In the system, the traffic of a UE can be offloaded to another UE with an offload coefficient. Let Ω denote the set of offload coefficients from UE_m to UE_n with $\Omega \triangleq \{\omega_{1n}, \dots, \omega_{mn}\}; m, n \in \mathcal{M}, n \neq m$, where $0 \leq \omega_{mn} \leq 1$.

The BSs are assumed to be aware of each other's channel gains: g_m (the channel gain between UE_m and the BS), g_n (the channel gain of the link between the BS and UE_n), and g_{mn} (the channel gain between UE_m and UE_n). Channel gain is calculated as the inverted path loss. Please note that in our case, the path loss of the link between the BS and the UE and the path loss of the link between one UE and another UE are modeled based on the macro-to-UE model, and on A1-type generalized path-loss models in the frequency range 2-6 GHz developed by the 3rd Generation Partnership Project (3GPP) [61] and WINNER II [62], respectively.

In the system, the amount of data of UE_m can be transmitted to UE_n with N_m packets and bandwidth BW . The amount of data of the link from UE_m to UE_n is calculated as total data of the offloaded transmission from UE_m to UE_n (λ_{mn}^o) and the transmission from UE_m to UE_n (λ_{mn}^c) via the BS. On the other hand, in no-offload transmission, the amount of data of the link from UE_m to UE_n is only calculated as the transmission from UE_m to UE_n (λ_{mn}^c) via the BS with an offload coefficient equal to zero. Therefore, the amount of data from UE_m to UE_n is defined as follows:

$$\lambda_{mn} = \lambda_{mn}^o + \lambda_{mn}^c \quad (6)$$

where λ_{mn}^o is the amount of data of the offloaded transmission between UE_m and UE_n which is given as follows:

$$\lambda_{mn}^o = \omega_{mn} N_m BW \log_2 (1 + \gamma_{mn}) \quad (7)$$

where ω_{mn} is the offload coefficient from UE_m to UE_n , and γ_{mn} is signal-to-interference-plus-noise ratio (SINR) for transmission from UE_m to UE_n , which is shown as:

$$\gamma_{mn} = \frac{P_m g_{mn}}{P_{BS} g_n + \sum_{i \in \mathcal{M} \setminus \{m,n\}} P_i g_{in} + \sigma^2} \quad (8)$$

where P_m is UE_m 's power for the offloaded transmission, P_{BS} is the BS's transmission power, and σ^2 is the estimated noise level.

In a BS-based transmission process, UE_m uses ω_{mn} of the amount of data for offloading transmission to UE_n , and UE_m will use the remaining $(1 - \omega_m)$ of the amount of data for BS-based transmission to UE_n . When the decode-and-forward (DF) scheme is used, the amount of data for the BS-based transmission is defined as follows:

$$\lambda_{mn}^c = (1 - \omega_{mn}) N_m \min \{\lambda_{mBS}, \lambda_{BSn}\} \quad (9)$$

where λ_{mn}^c is the amount of data of the transmission from UE_m to UE_n via the BS; λ_{mBS} is the amount of data between UE_m and the BS, and λ_{BSn} is the amount of data between the BS and UE_n , which are given as:

$$\lambda_{mBS} = BW \log_2 (1 + \gamma_{mBS}) \quad (10)$$

$$\lambda_{BSn} = BW \log_2 (1 + \gamma_{BSn}) \quad (11)$$

where γ_{mBS} is the SINR for transmission from UE_m to the BS, and γ_{BSn} is the SINR for transmission from the BS to UE_n , represented as follows:

$$\gamma_{mBS} = \frac{P'_m g_m}{\sum_{i \in \mathcal{M} \setminus \{m\}} P_i g_i + \sigma^2} \quad (12)$$

$$\gamma_{BSn} = \frac{P_{BS} g_n}{\sum_{i \in \mathcal{M} \setminus \{n\}} P_i g_{in} + \sigma^2} \quad (13)$$

where P'_m is UE_m 's transmission power for BS-based transmission.

For a fair comparison in offloading and BS-based transmissions, UE_m is assumed to use the same power for offloading transmission and BS-based transmission to UE_n . Therefore, we can get:

$$P'_m = \frac{\omega_{mn}}{(1 - \omega_{mn})} P_m \quad (14)$$

4. Problem Formulation for MDO Based on NBS with Game Model

The MDO problem based on game theory with an NBS is defined by $\mathcal{G} = (\mathcal{I}, S_i, \phi_i), \forall i \in \mathcal{I}, \mathcal{I} = \{1, 2, \dots, I\}$ where I is the number of players and is also the number of link pairs between UE_m and UE_n . S^* is a set of possible strategies for each players, and $\Phi = (\phi_1, \dots, \phi_i, \dots, \phi_I)$ is a set of the payoffs for link pairs between UE_m and UE_n , where ϕ_i is the payoff function for player p_i . The payoff for each player represents the cost that player p_i must endure for taking an action, $S_i^{opt} = \omega_{mn}^{opt}$.

i. Players (p_i): The link pairs between UE_m and UE_n , $\mathcal{P} = (p_1, \dots, p_i, \dots, p_I), \forall i \in \mathcal{I}$.

- ii. **Strategies** (S^*): Each link pair of m and n has a set of possible actions, $S^* = (S_1^{opt}, \dots, S_i^{opt}, \dots, S_I^{opt})$, where $S_i^{opt} = \omega_{mn}^{opt}, \forall m, n \in \mathcal{M}, n \neq m$, and $0 \leq \omega_{mn}^{opt} \leq 1$ that represents the strategy space for player p_i .
- iii. **Payoff function** $\phi_i(\lambda_{mn})$: This defines the total cost for a link pair between UE $_m$ and UE $_n$ at amount of data of λ_{mn} in a mobile environment. The payoff function is defined to include the profit (the utility function), the energy consumption, and a network connecting cost (i.e., monetary cost) presented as follows:

- **Monetary cost** (C_{mn}) represents the cost the UE pays based on the maximum K amount of data the UE uses on any given provider. Because the payoff function is calculated based on different functions that include the utility function, energy consumption function, and monetary cost, these functions should be transferred into the normalized form. In normalized form, it is assumed that if a UE uses the amount of data K for transmission, the monetary cost should be transferred to a payoff unit. Therefore, in this paper, if a UE uses the amount of data λ_{mn} for transmission, the monetary cost transferred to a payoff unit as follow:

$$C_{mn} = \frac{\lambda_{mn}}{K} \quad (15)$$

- **Utility function** ($U_{mn}(\lambda_{mn})$) represents the profit of player p_i for using strategy ω_{mn} :

$$U_{mn}(\lambda_{mn}) = \alpha \log(\lambda_{mn} + C) - \log(\lambda_{req}^{min}) \quad (16)$$

where λ_{mn} is the total amount of data of UE $_m$, which is given in (6); α is a user-defined factor; C is a safety constant to make sure there is always a defined value for the utility function; and λ_{req}^{min} is the required minimal transmission data. In normalized form, if UE $_m$ uses amount of data λ_{mn} for transmission to UE $_n$, the utility function will be transferred to a payoff unit ($C_{U_{mn}}$), which is used to calculate the payoff of each link pair. The cost of utility function is represented as follows:

$$C_{U_{mn}} = \frac{U_{mn}(\lambda_{mn})}{U_{mn}(K)} \quad (17)$$

where $U_{mn}(K)$ is the normalized function with amount of data K for the utility function which is defined by $U_{mn}(K) = \log(K + C)$.

- **Energy consumption function** ($E_s(\lambda_{mn})$) is one of the most important factors in many network applications with a high cost to replace batteries. When data packets are sent from the source node to the sink node, energy consumption is generated. More packet transmissions means a higher data rate and higher energy consumption. Another factor that affects energy consumption is the density of the network; the more UEs with additional packet transmissions, the higher the density of the network, and thus, the higher the energy consumption. The energy consumption function is defined as follows:

$$E_s(\lambda_{mn}) = \beta D_{me} \lambda_{mn} \quad (18)$$

where β is a user-defined factor given for the energy-saving requirement, and D_{me} is the density metric of the network. We can express the network density in terms of the number of UEs per nominal coverage area. Thus, if M UEs are scattered in area A , and the nominal range of each UE is R , the density metric will be given as follows [63]:

$$D_{me} = \frac{|M| \pi R^2}{A} \quad (19)$$

where A is transmission area of macro BS which is defined by $A = 4r^2$ with r is transmission radius of macro BS.

The cost of energy consumption function (C_{Es}), which based on the normalized form, is calculated as:

$$C_{Es} = \frac{E_s (\lambda_{mn})}{K} \quad (20)$$

For each player p_i , the payoff function based on the normalized form can be declared as:

$$\phi_i (\lambda_{mn}) = C_{U_{mn}} - C_{Es} - C_{mn} \quad (21)$$

Let $E_{re}(t)$ denote the remaining-energy function. The UE updates its remaining energy for time slot $t + 1$. $E_{re}(t)$ is the amount of energy remaining in the battery in the t th time slot. When the updated energy of the UE is less than the energy consumption, the UE will not have enough energy to transmit data, and will harvest energy from an ambient non-RF signal. Conversely, if the UE has enough energy to transmit data (i.e., $E_{re}(t) + e^{hv}(t) \geq E_s$), it will transmit data to another UE. The updated remaining energy for the next time slot is calculated by:

$$E_{re}(t+1) = \min \left\{ \max \left\{ E_{re}(t) + e^{hv}(t) - E_s, 0 \right\}, E_{bat} \right\} \quad (22)$$

When the remaining energy of the UE is updated, the payoff function of each player is also updated over t time slots. Then, in this paper, the final payoff is obtained by averaging the payoffs over $N_{timeslot}$, which is used as a set of the payoffs with the NBS for the MDO problem.

To find a solution to the game, $\mathcal{G} = (\mathcal{I}, S_i, \phi_i)$, $\forall i \in \mathcal{I}$, a proof that it has a unique solution is required, and this means that each player can reach an optimal strategy, $S_i^{opt} = \omega_{mn}^{opt}$, where it has no incentive to change its strategy given that all other players maintain their current strategies. There exists a unique and optimal NBS, which was proved in [56]. The Nash bargaining problem, which determines optimal offload coefficient ω_{mn}^{opt} , such that the NBS payoff function can be maximized (for example, by using advanced novel optimization techniques proposed in [36,64,65]) for this game, is presented as follows:

$$S^* = \max_{S_i^{opt}} \prod_{i=1}^I (\phi_i - \phi_i^{min}) \quad (23)$$

$$\text{s.t. } \phi_i \geq \phi_i^{min} \quad (24)$$

$$0 \leq \omega_{mn}^{opt} \leq 1 \quad (25)$$

Moreover, in order to evaluate how fairly the resources are distributed among existing D2D-link pairs, we use the Jain's fairness index [25] as a fairness index (FI) as follows:

$$FI = \frac{\left(\sum_{i=1}^I \phi_i \right)^2}{I \sum_{i=1}^I \phi_i^2} \quad (26)$$

In section of simulation results, we will evaluate the fairness of network with this fairness index. In addition, in the MFI scheme, one of baselines scheme, UEs will offload data traffic to another UE such that the fairness index of the network can be maximized as follows:

$$\omega_{mn}^* = \max_{\omega_{mn}^{opt}} FI \quad (27)$$

$$\text{s.t. } 0 \leq \omega_{mn}^{opt} \leq 1 \quad (28)$$

5. Simulation Results

In this section, we present simulation results and discussions to verify the efficiency of the proposed game scheme. In order to see the domination of the proposed scheme, we compare the performance of the proposed game scheme those of two baseline schemes; the MFI scheme and the no-offload scheme. In the MFI scheme, UEs can also offload data traffic to another UE, and the fairness index of the network is maximized such that link pairs receive a fair payoff. In the no-offload scheme, UEs will transmit data to other UEs through the BS with offload coefficients of zero. We employ performance metrics (average throughput, FI value, sum of payoff value, and EE) in the performance evaluation with various network conditions, such as mean value of harvested energy, and offload coefficient with changing of required minimal transmission data. The FI is defined as a value to determine if link pairs are receiving a fair share of the payoff from the system. In these simulations, we assume a macro BS is located in the center of a typical macro cell with a radius of 180 m, and four UEs are randomly distributed throughout the macro cell. Bandwidth and frequency of the RF signal are set at 1 MHz and 2 GHz, respectively. In addition, we set the path-loss models based on macro-to-UE and A1-type generalized path-loss models developed by the 3GPP [61] and WINNER II [62], respectively. The minimal payoff to link pairs is set at 0. Algorithm 1 is used to find the optimal offload coefficient for MDO, and the value of other parameters used in the simulation are listed in Table 1.

Algorithm 1 Find optimal offload coefficient

```

1: Initialization: Set parameters:  $M, R, A, P_{BS}, P_m, N_m, BW, K, N_{timeslot}, \alpha, \beta, C, E_{bat}, E_{re}(1) = 0$ 
2: Input:  $e^{hv}(t), E_{re}(t), S = (S_1, \dots, S_i, \dots, S_I)$ , where  $S_i = \omega_{mn}, \forall m, n \in \mathcal{M}, n \neq m$ , and  $0 \leq \omega_{mn} \leq 1$ 
3: Output: Optimal offload coefficients  $(\omega_{mn}^{opt})$ , evaluation metrics (FI value, average throughput, EE).
//In the first timeslot ( $t = 1$ ):
4: For  $\omega_{mn} = 0, 0.1, \dots, 1$ 
5:   Calculate  $\lambda_{mn} \leftarrow (6)$ 
6:   Calculate normalization money cost:  $C_{mn} \leftarrow (15)$ 
7:   Calculate normalization utility:  $C_{U_{mn}} \leftarrow (17)$ 
8:   Calculate normalization energy consumption:  $C_{E_s} \leftarrow (20)$ 
9:   Calculate payoff function:  $\phi_i(\lambda_{mn}) \leftarrow (21), \forall m, n \in \mathcal{M}, n \neq m, \forall i \in \mathcal{I}, \mathcal{I} = \{1, 2, \dots, I\}$ .
10: EndFor
//Calculate for the next timeslots:
11: For  $t = 2, 3, \dots, N_{timeslot}$ 
12:   Update  $E_{re}(t) \leftarrow (22)$ 
13:   If  $E_{re}(t) < 0 (E_{re}(t-1) + E^{hv}(t-1) < E_s)$ 
14:     Update:  $\lambda_{mn}^t = C_{mn}^t = C_{U_{mn}}^t = C_{E_s}^t = \phi_i^t(\lambda_{mn}) = 0$  at the timeslot  $t$ 
15:   Else  $(E_{re}(t-1) + E^{hv}(t-1) \geq E_s)$ 
16:     Update  $\lambda_{mn}^t = \lambda_{mn}^{t-1}, C_{mn}^t = C_{mn}^{t-1}, C_{U_{mn}}^t = C_{U_{mn}}^{t-1}, C_{E_s}^t = C_{E_s}^{t-1}, \phi_i^t(\lambda_{mn}) = \phi_i^{t-1}(\lambda_{mn})$ 
17:   EndIf
18: EndFor
19: Calculate the average of  $\lambda_{mn}, C_{mn}, C_{U_{mn}}, C_{E_s}, \phi_i(\lambda_{mn})$  through  $N_{timeslot}$ 
//Proposed game scheme:
20: Find optimal offload coefficients:  $S_i^{opt} = \omega_{mn}^{opt} \leftarrow (23), (24), (25)$ 
21: Return evaluation metrics with  $\omega_{mn}^{opt}$ 
//MFI scheme as one of baseline scheme for performance comparison:
22: Calculate FI value:  $FI \leftarrow (26)$ 
23: Find optimal offload coefficients:  $\omega_{mn}^* \leftarrow (27), (28)$ 
24: Return evaluation metrics with  $\omega_{mn}^*$ 
//No-offload scheme as one of baseline scheme for performance comparison:
25: Return evaluation metrics with  $\omega_{mn} = 0$ 

```

Table 1. Simulation parameters

Parameter	Description	Value
	Path-loss BS—UE (dB): $128.1 + 37.6\log_{10}d$ (km)	
	Path-loss UE—UE (dB): $38.4412 + 20\log_{10}d$ (m)	
N_m	Data transmission duration of UEs	100, 150, 32, 80
BW	Bandwidth	1 Mhz
M	The number of UEs	4
E_{bat}	Battery capacity	120 packets
e_{mean}^{hv}	Mean of harvested non-RF energy	9, 10, 11, 12 packets
P_{BS}	Transmission power of the BS	46 dBm
$P_1 - P_4$	Transmission power of UEs	15, 10, 19, 25 dBm
K	The normalized data	1 packet
α	A user-defined factor	4.7
β	A user-defined factor	0.01
C	The safety constant	0.1
R	Transmission range	400 m
A	The transmission area of macro BS	129,600 m ²
$N_{timeslot}$	The number of timeslots	1000

5.1. Performance from Various Mean Values of Harvested Non-RF Energy

We first observe the effect of harvested non-RF energy on network performance for all considered schemes. We compare the performance of the proposed game scheme in terms of FI value, average throughput, and sum of payoff value that of the schemes for MFI and no-offload when mean values of the harvested non-RF energy is changed. The simulation environment is the same, but the required minimal transmission data is chosen at 1 Mbps. The simulation results in terms of FI value, average throughput, and sum of payoff value under the various mean values of harvested non-RF energy are illustrated in Figures 3–5.

Figure 3. The influence of mean harvested non-RF energy on FI value of the network when mean value of harvested non-RF energy is changed from 9 to 12 packets.

In Figure 3, we observe the FI value of the network with increasing values of harvested non-RF energy. The Figure 3 shows that the FI value of the no-offload scheme has a downward trend, i.e., all three schemes have lower FI values as the mean value of harvested non-RF energy e_{mean}^{hv} is increased from 9 packets to 12 packets. Moreover, the FI values of the proposed game scheme and the MFI scheme has a slight drop when e_{mean}^{hv} is increased. However, they almost remain at a high FI value. In a nutshell, the FI value for all the schemes almost always degrades as e_{mean}^{hv} increases. This is because the more energy the UEs harvest, the larger the difference among payoffs for existing D2D-link pairs for which resources will be unfairly allocated.

In Figures 4 and 5, we compare the average throughput and sum of payoff values of three schemes (the proposed game, MFI, and no-offload) when the mean value of harvested energy is increased from 9 packets to 12 packets. Overall, the three schemes mostly have an upward trend in average throughput and sum of payoff values as e_{mean}^{hv} increases. This is because the transmissions by UEs are more effective when the total amount of harvested non-RF energy becomes larger. When e_{mean}^{hv} is small such as 9 packets, UEs only use a small amount of transmission energy, and thus, get a small value in average throughput and sum of payoff. When e_{mean}^{hv} is more than 11 packets, however, there is a significant increase in both average throughput values and sum of payoff values under the three schemes. In particular, when e_{mean}^{hv} is 11 packets, the average throughput of the proposed scheme provides improvements of 25.12% and 77.99% over MFI and no-offload schemes, respectively, and the sum of payoff values of the proposed scheme improve 32.2% and 82.03% over MFI and no-offload schemes, respectively. The proposed game scheme has the highest average throughput and sum of payoff among the three schemes, and the no-offload scheme has the lowest one.

Figure 4. The influence of mean harvested non-RF energy on average throughput of the network when mean value of harvested non-RF energy is changed from 9 to 12 packets.

5.2. Effect of the Offload Coefficients on Network Performance

The rest of the simulations are devoted to considering the impact of the offload coefficients. To do this, we use simulation environments similar to the previous simulation, done in Section 5.1, except that the mean value of harvested non-RF energy is changed ($e_{mean}^{hv} = 15$ packets) with which we can ensure enough transmission energy for the UEs.

Figure 5. The influence of mean harvested non-RF energy on total payoff of the network when mean value of harvested non-RF energy is changed from 9 to 12 packets.

The simulation results are given in Figures 6–9 with which we can observe further insights on the effect of offload coefficients on network performance.

Figure 6. The FI value according to offload coefficient pairs of the link between UE₂–UE₃ (ω_{23}) and the link UE₁–UE₄ (ω_{14}) when the minimum required data rate is 10 Mbps and 50 Mbps, respectively, and $e_{mean}^{hv} = 15$ packets.

Figure 7. The average throughput according to offload coefficient pairs of the link between UE₂–UE₃ (ω_{23}) and the link UE₁–UE₄ (ω_{14}) when the minimum required data rate is 10 Mbps and 50 Mbps, respectively, and $e_{mean}^{hv} = 15$ packets.

Figure 8. The sum of payoff according to offload coefficient pairs of the link between UE₂–UE₃ (ω_{23}) and the link UE₁–UE₄ (ω_{14}) when the minimum required data rate is 10 Mbps and 50 Mbps, respectively, and $e_{mean}^{hv} = 15$ packets.

Figure 6 shows the FI value versus the offload coefficient for the link between UE₂ and UE₃ (ω_{23}) when the minimum required data rate is 10 Mbps and 50 Mbps, respectively, and $e_{mean}^{hv} = 15$ packets. When the minimum required data rate is 10 Mbps, the FI value of the proposed game and the MFI scheme obtain maximal values of 0.8561 and 0.9961, respectively with optimal offload coefficient pairs $\omega_{23} = 0.6, \omega_{14} = 0.7$ and $\omega_{23} = 0.6, \omega_{14} = 1$, respectively. In the no-offload scheme, we just consider offload coefficients $\omega_{23} = 0, \omega_{14} = 0$, and the obtained FI value in this case equals 0.5144. Moreover, the required minimal transmission data of 50 Mbps is considered to show the decreasing FI value when the required minimal transmission data increases from 10 Mbps to 50 Mbps. The reason is when the required minimal transmission data is increased, the payoff degrades, which creates unfairly resource allocation among link pairs, and thus, gives the smaller FI value. Although the FI value of the MFI scheme is higher than that of the proposed game scheme due to the characteristic of maximized FI in the MFI scheme, but FI values of the proposed scheme almost remain at a high value.

Figures 7 and 8 show the effect of the offload coefficients on average throughput and sum of payoff values. The simulation results show that the performance of the proposed game scheme is more dominant in both average throughput values and sum of payoff values than MFI and no-offload schemes. In particular, the proposed game scheme has the highest value on average throughput and sum of payoff value for the three schemes. In Figure 7, average throughput values are not changed when minimal required data changes from 10 Mbps to 50 Mbps, but sum of payoff values are changed in Figure 8. This is because minimal required data just impacts on utility function, and accordingly on payoff value. More specifically, Figure 8 shows that the proposed scheme provides higher payoff values when the minimum required data rate is 10 Mbps, compared to the case when the minimum required data rate is 50 Mbps. This can be easily explained that when the required minimal transmission data is increased, the utility from the payoff will be degraded, which makes sum of payoff value decrease.

Figure 9. The energy efficiency (EE) according to offload coefficient pairs of the link between UE₂–UE₃ (ω_{23}) and the link UE₁–UE₄ (ω_{14}) when the minimum required data rate is 10 Mbps and 50 Mbps, respectively, and $e_{mean}^{hv} = 15$ packets.

Moreover, we also consider EE in the performance evaluation which is defined as the cost of utility function over the cost of energy consumption function. Figure 9 shows the EE according to the offload coefficient for the link between UE₂ and UE₃ (ω_{23}) when the minimum required transmission data is given as 10 Mbps and 50 Mbps, respectively. The EE of the proposed game scheme is better than that of MFI and no-offload schemes. In Figure 9, when the minimal transmission data is given as 10 Mbps, the proposed game and MFI scheme have obtained maximum EE of 26.41 and 24.86, respectively, at optimal offload coefficient pairs $\omega_{23} = 0.6, \omega_{14} = 0.7$ and $\omega_{23} = 0.6, \omega_{14} = 1$, respectively. In the no-offload scheme, with offload coefficients $\omega_{23} = 0, \omega_{14} = 0$, we can get EE of 22.66. It is obvious that the EE is decreased at the required minimal transmission data of 50 Mbps, compared to the case when the required minimal transmission data is 10 Mbps. This can be explained that when the required minimal transmission data is increased, the cost of utility function will be degraded, which makes EE decrease.

6. Conclusions

In this paper, we study the problem of MDO via D2D links along with considering NRF-EH where mobile data of a user is offloaded to another user with an offload coefficient. We propose a game scheme using the NBS where each link counts as a player in order to optimize network performance in terms of FI value, throughput, and EE while considering fairness among the links. Simulation results show that the proposed game scheme can effectively offload data, achieves better EE, and improves throughput while maintaining high fairness in the network, compared to the MFI and no-offload schemes under network parameters such as mean of harvested non-RF energy, and offload coefficients.

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