Multi-Operator Collaboration for Green Cellular Networks

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Abstract

This chapter investigates the collaboration between multiple mobile operators for optimizing energy efficiency in cellular networks. Most of the works in the literature optimize the performance of a given cellular network, without considering the existence of mobile networks belonging to other operators. This leads to suboptimal results, compared to the case where the optimization of the joint performance of mobile networks of multiple operators is considered. However, incentives need to be created to allow multiple (and generally competing) operators to collaborate for the purpose of energy efficiency. Indeed, random collaboration can cause certain unfairness among cooperative operators. Therefore, additional parameters should be considered to perform a fair green networking between mobile operators. This chapter aims to provide answers for similar situations. We start by investigating the case of uniform cooperative mobile operators having the same objectives and we establish cooperation decision criteria based on derived roaming prices and operators' profit gains. Afterwards, we consider the case of non-uniform operators where a green operator focuses on exploiting the infrastructure of non-green operators to achieve CO_2 emissions saving. A two-level Stackelberg game is formulated to optimize the utilities of both types of operators.

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1 Introduction

Over the years, mobile user demand is witnessing an unprecedented rise that is leading to an enormous growth of energy consumption of wireless networks as well as the greenhouse gas (GHG) emissions which are estimated currently to be around 70 million tons over a year [1]. The huge increase of number of connected terminals, in addition to the deployed infrastructure necessary to serve them, impels network companies to pay enormous bills which represent about 50% of their operating expenditures (OPEX). Therefore, the reduction of the network energy consumption and the limitation of their CO_2 emissions and their energy expenses becomes more and more attracting the researchers' attentions [2]. Many studies were proposed to develop green communication systems which can save energy consumption and reduce CO_2 emissions [3, 4]. Most of them tackle the radio access network part as base stations (BSs) consume more than $70-80\%$ of the total power consumption [5]. Half of this energy is redundant especially during off-peak periods when these BSs are underused [6]. To overcome this issue, new system level features were designed to help decide which parts of the redundant BS should be turned off. Therefore, subscribers, who were covered by an underutilized BS, will be served by another BS [7] or even by other operator's infrastructure [8] in the context of green mobile operator networking.

Several schemes have focused first on the optimization of the energy consumption of the radio access network part by turning off redundant BSs during low traffic period while considering the network quality of service (QoS). In [9, 10], the BS ON/OFF strategy is applied in order to eliminate underutilized BSs while optimizing QoS utility functions. The authors of [11] proposed an efficient green planning method based on the spatial and temporal traffic variations where the BSs needed to be activated during a certain period of the day are identified since the network planning phase. To turn off a BS, the authors of [12] calculated the joint Signal to Interference plus Noise Ratio (SINR) corresponding to the sum of SINRs of all subscribers in the network and compared it to a fixed SINR threshold: If it is higher than the threshold, the selected BS to be switched off is underutilized and is maintained off. Another BS sleeping strategy is presented in [13] where an approximate solution to the problem was proposed. The main idea is to establish a relationship between the traffic load (user arrival) and energy savings. An optimization problem aiming to minimize the number of active BSs subject to two constraints: Maintaining the user connection in the cell and covering the same initial area is solved.

Another approach to ensure energy savings for wireless cellular networks is to investigate the energy-efficient communications while considering the dynamics of the smart grid that depend on the traffic, real-time price and the pollutant level associated with the generation of the electricity. The authors in [14] introduced the use of coordinated multipoint communication (CoMP) to ensure acceptable QoS in cells whose BSs have been shut down to save energy. Meanwhile, the active BSs decide from which energy sources and how much energy they need to procure in order to ensure the safe operation of the network. This is performed while taking into account the pollutant level of each retailer and the proposed price. The scheme proposed in [14] could reduce operational expenditure and CO_2 emissions in green wireless cellular networks.

Optimizing the joint utilities of different mobile networks serving the same area provides more degrees of freedom for mobile operators to achieve green communication [7]. The fundamental idea was to completely switch off the equipment of a service provider while serving the corresponding subscribers by another infrastructure belonging to another operator under some fairness constraints. In Fig. 1, we illustrate an example of mobile operator collaboration where an operator (Operator 1 in red) exploits the other mobile operator's infrastructure (Operator 2 in black) to serve its subscribers while turning off its own BS and vice versa. However, this operation would eventually require the introduction of certain incentives in order to ensure fairness among competitive mobile operators. In literature, few research work had focused on the mobile operator cooperation for green purposes. One of the first studies in this field was proposed in [8, 15]. In [15], the authors identified four different sleeping strategy schemes such as balanced roaming costs and balanced energy savings. The authors in [8, 16] have improved the operator cooperation problem by modeling it in a game-theoretical strategy that ensures energy saving by eliminating lightly loaded BSs. In [17], the green collaboration between mobile operators powered by multiple energy retailers existing in the smart grid is investigated. A Stackelberg game theoretical approach is employed to model the smart grid real-time pricing of the energy procurement.

However, the discussed solutions only examine one aspect of the problem each time and do not include neither long term evolution advanced (LTE-A) nor the aspects of renewable energy and collaboration expenses in the problem formulation. Furthermore, most of the proposed green networking schemes do not consider the collaboration cost. Indeed, although collaboration among mobile operators provide more flexibility in achieving green performance compared to the traditional scenario, random collaboration would be unfair for one or a group of operators. For instance, one operator might turn off all the BSs and all the users are roamed to the infrastructure belonging to competitive operators. Hence, the serving operator might suffer from a high energy consumption while the first operator is enjoying its profit increase. While this solution maximizes the overall objective of operators, the individual objective distribution is not fair. Therefore, it is important to introduce some fairness criteria during the cooperation process. These criteria will influence the collaboration decision of operators. These fairness criteria can take different forms such as the collaboration under equal charge allocation where the total cost is equally shared among operators [8]. Another fairness criterion could be the equal share of the collaboration cost. In this case, only the cost due to collaboration is considered and shared among operators. Note that these fairness criteria force operators to be a member of the collaboration group and share the cost with other competitive operators. In our study, we propose a fairness criterion based on roaming prices defined by each operator who is willing to serve users of competitive operators. The proposed method will also allow operators to decide whether to enter in collaboration or not. This decision is made after checking whether the total profit of this operator is affected due to collaboration or not.

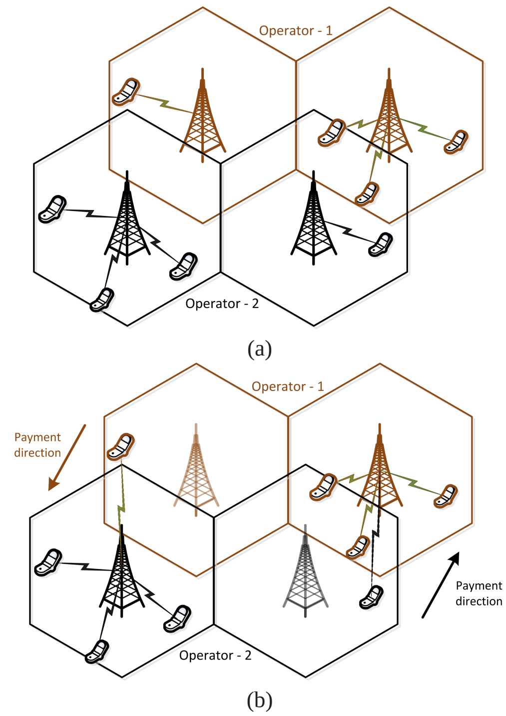

Fig. 1: Example of mobile operator collaboration: (a) without collaboration; (b) with collaboration.

In this chapter, we propose to investigate the collaboration among multiple mobile operators deploying LTE-A networks in the same area. The objective is to study the interactions among competitive mobile operators collaborating together in order to achieve green goals without compromising their profits and QoS. Two scenarios are investigated in this chapter: The first one considers the case of uniform mobile operators having the same green objectives, while the second one investigates the case of non-uniform operators having different objectives. In the first scenario, a practical and low complexity iterative algorithm is applied to determine the efficient active BS combination that ensures energy saving while respecting the network QoS. The BSs are assumed to be powered by either traditional retailer and/or renewable energy equipment (e.g., solar panel or wind turbine) owned by mobile operators and placed on BS sites. During this cooperation, extra charge can be added to operators that keep their BSs active as they are serving other mobile operators' subscribers. Therefore, a fairness criterion for mobile operator cooperation based on their profits before and after cooperation is introduced. Finally, the roaming prices for all operators and conditions for cooperation decision are also proposed.

Afterwards, we investigate the case of non-uniform mobile operators having different objectives: One green operator (GO) that aims to achieve a tradeoff between its profit and its network CO_2 emissions and other non-green operators (NGOs) available to serve green operator's users in order to enhance their profits. The GO's BSs are powered by either a traditional electricity retailer or renewable energy equipment. We employ a two-level Stackelberg game that helps the GO (playing the role of the follower) reduce its energy consumption and CO_2 emissions by roaming some of its users to one or many NGOs (playing the role of leaders). The GO can either offload all the users of a BS and switch it off or just offload some of them. However, during cooperation, extra charge will be imposed on the GO when exploiting another NGO's infrastructure to serve its subscribers. The NGO's objective is to maximize its own profits by attracting the maximum number of GO roamed users. In this competition, the leaders focus on offering the best roaming prices while taking into account multiple system parameters (e.g., energy cost and pollution level, service fee, GO renewable energy availability, etc.). We solve this problem by achieving the Stackelberg equilibrium and investigate the player behaviors for various system parameters.

In our simulation result section, we investigate the impact of several parameters on the system performance such as the traffic volume, availability of locally generated green energy, and energy cost. We also show that mobile operator collaboration can significantly contribute in reducing the carbon footprint of cellular networks.

This chapter is organized as follows. Section 2 investigates the case of uniform mobile operators collaboration. Section 3 discusses the case of the collaboration of non-uniform mobile operators. In Section 4, we present our simulation results for both studied settings and provide some insights about the future challenges of green networking. Finally, Section 5 summarizes the chapter.

2 Collaboration of Uniform Mobile Operators

In this section, we focus on the collaboration among uniform mobile operators having similar goals, i.e., reduce their fossil fuel consumption. Each mobile operator tries to turn off the maximum number of BSs in order to achieve energy saving but without affecting the QoS. The QoS is maintained thanks to intra and inter operator collaboration. Indeed, the users previously connected to a turned off BS are offloaded to neighbor BSs which belong either to the same operator or to a competitive one. However, in order to avoid random collaboration, which might lead to negative impacts on one of the operator performance, a fairness criterion based on the roaming price is proposed. This criterion will determine whether collaboration is beneficial for all operators or not. A thorough version of this work with additional mathematical details is presented [18].

2.1 System Model

We assume N_{op} mobile operators are deploying N_{op} LTE networks that satisfies the traffic demands of its customers and covers a geographical area of interest. We denote by $N_{BS}^{(n)}$ the number of BSs that are deployed uniformly by the mobile operator n in that area, $n = 1, \cdots, N_{\text{op}}$. We consider that the area is divided into cells of equal size where a BS is placed in the center of each cell. The access scheme for the LTE downlink (DL) is the orthogonal frequency division multiple access (OFDMA) while in the uplink (UL), the single carrier frequency division multiple access (SC-FDMA) is used. In fact, the DL and UL available spectrums are divided into N_{RB} resource blocks (RBs) that contain a fixed number of consecutive subcarriers ($N_{\text{RB}} = N_{\text{RB}}^{(\text{UL})} = N_{\text{RB}}^{(\text{DL})}$). RBs are assigned to users according to the resource allocation procedure followed by each operator. We assume that the mobile operators are using different frequency bands such that there is no inter-operator inference. However, intra-operator interference is taken into account (i.e., frequency reuse of 1 is assumed within each operator's network). In this section, the considered channel gain for both directions (UL and DL) captures the pathloss, shadowing, and fading effects. More details about the channel model and the data rate expressions in DL and UL for LTE can be found in [4]. We assume that the subcarriers constituting a single RB are subjected to the same fading and hence the channel gain on the subcarriers of a single RB is considered to be the same. In addition, the fading is assumed to be independent and identically distributed (iid) across RBs. In this section, we allocate one UL RB and one DL RB for each user. First, we start by allocating DL subcarriers in order to save BS power usage, since usually the DL traffic is much heavier than UL traffic. Then, the DL and UL rates are computed using the typical Shannon rate expression.

2.1.1 Energy Consumption Model for Base Stations

We consider that each BS is equipped with a single omni-directional antenna. The consumed power of an active BS j belonging to mobile operator n, $P_j^{(n)}$, can be computed as follows [4]:

$$P_j^{(n)} = aP_{n,j}^{(\text{tx})} + b, \tag{1}$$

where the coefficient a corresponds to the power consumption that scales with the radiated power due to amplifier and feeder losses, and the term b models an offset of site power that is consumed independently of the average transmit power and is due to signal processing, battery backup, and cooling. In (1), $P_{n,j}^{(tx)}$ denotes the radiated power of the j^{th} BS belonging to operator n and can be expressed as follows:

$$P_{n,j}^{(\text{tx})} = \sum_{r=1}^{N_{\text{RB}}^{(\text{DL})}} P_{n,r}, \tag{2}$$

where $P_{n,r}$ is the power consumed per one RB and depends on the RB state. If the RB r of BS j is allocated to a certain user, then $P_{n,r} = \frac{P_{\text{tot}}}{N_{\text{RB}}^{(\text{DL})}}$, else $P_{n,r} = P_{\text{idle}} \approx 0.19$ dBm, [19]. If a BS j is completely switched off, we assume that its power consumption $P_j^{(n)} = 0$. To power its BSs, the mobile operator either procures energy from a traditional electricity provider or uses renewable energy generators installed on BS sites, e.g., solar panels or wind turbine. The amount of energy procured from the fossil fuel retailer and the auto-generated amount of energy consumed by BS j of mobile operator n are denoted by $q_j^{(n,f)}$ and $q_j^{(n,g)}$, respectively, where f and g stands for fossil fuel and green energy, respectively. The amount of green energy generated locally varies from one BS to another depending on technical and environmental reasons. For instance, the solar rating depends essentially on the size of photovoltaic (PV) panels and whether they experience any shading during the day.
Note that the locally generated energy is free of charge whereas the electricity procured from the external retailer is evaluated by $\pi^{(f)}$ where $\pi^{(f)}$ is the cost of one unit of energy. That is, the fossil fuel, $q_j^{(n,f)}$, procured by BS j belonging to mobile operator n is equal to the total power $P_j^{(n)}$ consumed by this BS multiplied by its operation time Δt minus the amount of renewable energy generated locally $q_j^{(n,g)}$. The objective of each mobile operator is to minimize the consumption of its fossil fuel in order to reduce its energy cost.

2.1.2 Operator Services

In our study, we consider M different services are offered by mobile operators to their subscribers. Each service is identified by the data rate thresholds $R_{m,th}^{(\text{UL})}$ and $R_{m,th}^{(\text{DL})}$ for UL and DL, respectively, and a unitary price $p^{(m)}$ with $m = 1, \cdots, M$. We suppose that each subscriber associated to the network n is using one of the M offered services. For simplicity, we assume that all mobile operators offer similar services to their corresponding subscribers.

The main objective of this study is to formulate an optimization problem that minimizes the total fossil fuel consumption of cellular networks operating in the same area of interest. The BS ON/OFF strategy in a cooperative fashion will be applied in order to achieve green goals. In this setting, we also aim to at least not degrade the network QoS and the profit of each mobile operator but rather enhance them. However, in some cases, although it helps in reducing the CO_2 emissions, cooperation might lead to a negative impact on the profit of one of the mobile operators. Therefore, we establish a fairness condition that indicates whether green networking is favorable to operators or not. Finally, we compare the performance of our proposed scheme with the traditional scenario where cellular companies operate individually without cooperations.

2.2 Green Uncooperative Operators

We start by evaluating the gain of applying the BS sleeping strategy separately for each operator in terms of energy saving and profit. Let $\varepsilon^{(n)}$ be a binary vector that indicates the states the n^{th} mobile operator BSs during the period Δt. Its elements $\varepsilon_j^{(n)}$ indicates whether a BS j of cellular company n is turned off or not as follows:

$$\varepsilon_j^{(n)} = \begin{cases} 1, \text{ if BS } j \text{ is turned on,} \\ 0, \text{ if BS } j \text{ is turned off.} \end{cases} \tag{3}$$

The number of ones and zeros in this vector indicates the number of active and inactive BSs, respectively. Thus, the fossil fuel consumption and the corresponding total cost of the n^{th} mobile operator, denoted by $\mathscr{E}^{(n)}$ and $\mathscr{C}^{(n)}$ respectively, are given as follows:

$$\mathscr{E}^{(n)} = \sum_{j=1}^{N_{\text{BS}}^{(n)}} \varepsilon_j q_j^{(n,f)}, \text{ and } \mathscr{C}^{(n)} = \pi^{(f)} \mathscr{E}^{(n)}. \tag{4}$$

On the other hand, we compute the mobile operator profit provided by the operating BSs in the area. It is exclusively computed from the number of served customers and the corresponding service. In fact, during Δt, each mobile operator n is serving $N_U^{(n)}$ mobile stations connected to the network and enjoying one of the M proposed services. We denote by $N_{\text{out}}^{(n)}$ the number of users in outage during a period of Δt where $N_{\text{out}}^{(n)} \ll N_U^{(n)}$. A user i using the m^{th} service communicates successfully with a BS if its UL and DL data rates, denoted by $R_i^{(\text{UL})}$ and $R_i^{(\text{DL})}$, are higher than the service data rate thresholds, $R_{m,th}^{(\text{UL})}$ and $R_{m,th}^{(\text{DL})}$ respectively. By denoting a binary parameter $\gamma_i^{(n)}$, $i = 1 \cdots N_U^{(n)}$, we can express this assumption as follows:

$$\gamma_i^{(n)} = \begin{cases} 1, \text{ if } R_i^{(\text{UL})} \geq R_{m,th}^{(\text{UL})} \text{ and } R_i^{(\text{DL})} \geq R_{m,th}^{(\text{DL})}, \\ 0, \text{ if } R_i^{(\text{UL})} < R_{m,th}^{(\text{UL})} \text{ or } R_i^{(\text{DL})} < R_{m,th}^{(\text{DL})}. \end{cases} \tag{5}$$

In other words, if $\gamma_i^{(n)} = 0$, then the i^{th} user fails to achieve its QoS during Δt. Let the vector $\gamma^{(n)} = [\gamma_1^{(n)} \cdots \gamma_{N_U}^{(n)}]$, then the number of ones and zeros in $\gamma^{(n)}$ corresponds to the number of served users and the number of users in outage, respectively. Consequently, only the served users pay the equivalent of the proposed service. Hence, the profit $\mathscr{P}_u^{(n)}$ of the n^{th} mobile operator corresponding to its individual operation in this area is expressed as follows:

$$\mathscr{P}_u^{(n)} = \sum_{i=1}^{N_U^{(n)}} \gamma_i^{(n)} p_i^{(n,m)} + R_{\text{op}} \left(N_U^{(n)} \right) - \mathscr{C}^{(n)}, \tag{6}$$

where $p_i^{(n,m)}$ is the unitary cost of the service m used by the i^{th} user of the n^{th} cellular company and R_{op} is a constant extra revenue due to fixed subscription fees paid by the mobile operator subscribers. Hence, the optimization problem for a single mobile operator n is expressed as follows:

$$\underset{\gamma^{(n)},\varepsilon^{(n)}}{\text{Minimize}} \quad \mathscr{E}^{(n)} = \sum_{j=1}^{N_{\text{BS}}^{(n)}} \varepsilon_j q_j^{(n,f)}, \tag{7}$$

$$\text{Subject to: } \frac{N_{\text{out}}^{(n)}(\gamma^{(n)})}{N_U^{(n)}} \leq P_{\text{out}}. \tag{8}$$

The unique constraint of the problem is (8) which forces the percentage of users in outage to be lower than an outage probability threshold P_{out}. This constraint is an output of the resource allocation algorithm applied for a given $\varepsilon^{(n)}$. It is very complex to find the optimal solution of this problem since the decision variables correspond to large binary vectors that depend on $N_U^{(n)}$ and $N_{\text{BS}}^{(n)}$. In [4], the authors proposed and compared deterministic and heuristic algorithms used to solve similar optimization problems for a single mobile operator scenario. They showed that the low complexity iterative algorithm achieves close performance to the evolutionary algorithms (e.g., genetic algorithm and particle swarm optimization approach) with a certain gain in terms of computational time. Hence, we employ the iterative algorithm to solve the formulated optimization problems in this section. Once optimization problem (7) is solved for each mobile operator n, we can deduce the corresponding profit $\mathscr{P}_u^{(n)}$ by computing (6) which has to be at least maintained in case of cooperative operation.

2.3 Green Cooperative Operators and Cooperation Decisions

In the cooperative mode, mobile operators can exploit the existence of other competitive providers in order to ensure energy saving and additional profit as well. In fact, instead of keeping lightly loaded BSs on, the mobile operator can turn them off and the subscribers may maintain their communication active using the radio access network of another operator serving the same area and vice versa. We propose to perform this by solving the following optimization problem where BS sleeping strategy is applied in order to achieve energy saving:

$$\underset{\gamma^{(n)},\varepsilon^{(n)},\, n=1,\cdots,N_{\text{op}}}{\text{Minimize}} \quad \sum_{n=1}^{N_{\text{op}}} \mathscr{E}^{(n)}, \tag{9}$$

$$\text{Subject to: } \frac{N_{\text{out}}^{(n)}(\gamma^{(n,1)},\cdots,\gamma^{(n,N_{\text{op}})})}{N_U^{(n)}} \leq P_{\text{out}}. \tag{10}$$

Once this optimization problem is solved using the iterative algorithm presented in [4], we obtain the optimal energy consumption under cooperative operation for each network and thus the optimal vectors $\gamma^{(n,t)}$ and $\varepsilon^{(n)}, n, t = 1, \cdots, N_{\text{op}}$. Comparing to (8), we notice that, in the cooperative case, $N_{\text{out}}^{(n)}$ depends also on the allocation over other mobile operators which are determined using $\gamma^{(n,t)}, t \neq n$. Indeed, thanks to the cooperation between mobile operators, some of users of mobile operator n can be served by another mobile operator t and vice versa. For this reason, we have introduced new binary vectors $\gamma^{(n,t)}$ of size $1 \times N_U^{(n)}$ that indicates whether a user of mobile operator n is served successfully by mobile operator t or not. This way, during the resource allocation algorithm, more degrees of freedom are provided for all users because of the increase of the number of RBs in the DL and UL directions. Thus, higher channel gains can be allocated and energy saving can be achieved. However, random cooperation may lead to the increase of a certain mobile operator profit at the expense of other competitive operators. This can cause a high energy consumption and a very low profit for the active network. For instance, a mobile operator A may switch off all its BSs while all its users are served by BSs owned by mobile operator B which pays all energy bills. For this reason, we enforce fairness by introducing the notion of roaming price that will allow any mobile operator to decide whether to cooperate or not.

In our study, we assume that the roaming price, denoted by p_{nt}, corresponding to the cost of serving users belonging to another operator is equal for every pairs of cooperative operators (n,t), i.e., $p_{nt} = p_{tn}$. In our framework, the profit of the cooperative mobile operator n denoted by $\mathscr{P}_c^{(n)}$ is expressed as follows:

$$\begin{aligned}\mathscr{P}_c^{(n)} = &\sum_{i=1}^{N_U^{(n)}} \gamma_i^{(n,n)} p_i^{(n,m)} + \sum_{\substack{t=1\\t\neq n}}^{N_{\text{op}}} \sum_{i=1}^{N_U^{(n)}} \gamma_i^{(t,n)} \left(p_i^{(n,m)} - p_{nt}\right) \\ &+ \sum_{\substack{t=1\\t\neq n}}^{N_{\text{op}}} \sum_{i=1}^{N_U^{(t)}} p_{nt} \gamma_i^{(t,n)} + R_{\text{op}}\left(N_U^{(n)}\right) - \mathscr{C}_c^{(n)},\end{aligned} \tag{11}$$

where the first term in (11) corresponds to the operator revenue coming from serving its own users while the second term is the revenue coming from users served by other mobile operators after paying the roaming cost. The third term in (11) is the gain obtained from serving users belonging to other networks which depends on p_{nt}. Finally, R_{op} is the constant revenue and $\mathscr{C}_c^{(n)}$ is the network energy consumption cost obtained after solving (9)-(10). A mobile operator n cooperates only if its cooperative profit $\mathscr{P}_c^{(n)}$ is greater than or equal to the uncooperative profit $\mathscr{P}_u^{(n)}$ expressed in (6). Thus, the operators have to solve the following non-homogenous system of N_{op} linear inequalities with $N_p = \frac{N_{\text{op}}\left(N_{\text{op}}-1\right)}{2}$ unknown variables:

$$\mathscr{P}_c^{(n)} \geq \mathscr{P}_u^{(n)}, \forall n = 1, \cdots, N_{\text{op}}. \tag{12}$$

We distinguish here two cases depending on the number of operators N_{op}:
- $N_{\text{op}} = 2$: In this particular case, we have two inequalities with one unknown variable p_{12}. For simplicity, let us denote $A_1 = \sum_{i=1}^{N_U^{(1)}} \gamma_i^{(1,1)} p_i^{(1,m)} + R_{\text{op}}\left(N_U^{(n)}\right) - \mathscr{C}_c^{(1)} + \sum_{i=1}^{N_U^{(1)}} \gamma_i^{(1,2)} p_i^{(1,m)}$, $A_2 = \sum_{i=1}^{N_U^{(2)}} \gamma_i^{(2,2)} p_i^{(2,m)} - \mathscr{C}_c^{(2)} + \sum_{i=1}^{N_U^{(2)}} \gamma_i^{(2,1)} p_i^{(2,m)}$, $B = \sum_{i=1}^{N_U^{(2)}} \gamma_i^{(2,1)}$ and $D = \sum_{i=1}^{N_U^{(1)}} \gamma_i^{(1,2)}$. Then, the system of inequalities can be written as follows

$$\begin{aligned} (B-D)p_{12} &\geq \mathscr{P}_u^{(1)} - A_1, \\ (D-B)p_{12} &\geq \mathscr{P}_u^{(2)} - A_2. \end{aligned} \tag{13}$$

Note that B corresponds to the number of users belonging to operator 2 served by operator 1 while D corresponds to the opposite situation. Thus, the problem solution depends on these variables. Indeed, if $B = D$, mobile operators do not need to impose a roaming price to each other and their profits are equal to A_1 and A_2, respectively. A simple comparison between $\mathscr{P}_u^{(n)}$ and $\mathscr{P}_c^{(n)}$ let them decide either they cooperate or no. Else (i.e., $B \neq D$), from (13), we distinguish two sets of possible solutions of p_{12}. If they are disjoint, cooperation is impossible. If there is an intersection interval, the operator collaboration is favorable for energy saving and profit enhancement. A fair choice of p_{12} is to maintain a close percentage change as follows:

$$\frac{\mathscr{P}_u^{(1)} - \mathscr{P}_u^{(2)}}{\mathscr{P}_u^{(1)}} \approx \frac{\mathscr{P}_c^{(1)}(p_{12}) - \mathscr{P}_c^{(2)}(p_{12})}{\mathscr{P}_c^{(1)}(p_{12})}. \tag{14}$$

- $N_{\text{op}} \geq 3$: In this case, the system can be written in the following matrix form:

$$A_{N_{\text{op}} \times N_p} p_{N_p \times 1} \leq b_{N_{\text{op}} \times 1}, \tag{15}$$

where A is a matrix that contains the coefficients of the system of linear inequalities while b is a vector that contains constant terms. p is the decision vector that is constituted by the roaming price $p_{nt}, n, t = 1, \cdots, N_{\text{op}}$. Each of the inequalities determines a certain half-space while all the inequalities together determine a certain region in the N_p-dimensional space which is the intersection of a finite number of half-spaces [20]. If this system admits a feasible solution (i.e., the system is said compatible), the mobile operator can cooperate safely without degrading neither their QoS nor their individual profits. If the system is incompatible, then the multi-operator collaboration is impossible. A system is said compatible if and only if, its concomitant system is compatible. Indeed, from the system (15), we can construct a concomitant system involving $N_p - 1$ unknowns after discarding the last unknown, and for this new system, we can construct another concomitant system involving $N_p - 2$ unknowns and so on. This way, after a number of steps, we construct a system consisting of inequalities of one unknown. Thus, the compatibility of the original system is determined from the compatibility of the last constructed concomitant system. Using the same steps detailed above, we can find a solution of the problem in case of compatibility. The set of solutions of this non-homogenous system can be also determined via different methods. (For more details, see [20]).

3 Collaboration of Non-Uniform Mobile Operators

After investigating the cooperation between uniform mobile operators having the same green objectives, we propose to investigate the collaboration between a green mobile operator and non-green operators with different utility functions. The green mobile company aims to achieve a tradeoff between its carbon dioxide emissions saving and its profit by exploiting the infrastructure of the non-green mobile companies existing in the same area. For the uniform scenario, the roaming price was based on mutual interests while in the non-uniform scenario, the non-green operators try to increase the roaming prices as much as possible in order to maximize their own profits. In [21], we present a thorough version of this work including more mathematical details.

3.1 System Model

We consider a geographical area served by $N_{\mathrm{op}}+1$ mobile operators. Each mobile operator is deploying an LTE network with N_{BS} BSs that satisfies the traffic demand of its customers and covers the total area (i.e., $N_{\mathrm{BS}}^{(1)} = \cdots = N_{\mathrm{BS}}^{(N_{\mathrm{op}})} = N_{\mathrm{op}}^{(0)}$; we set the index of the GO to 0). We assume that each cell is controlled by $N_{\mathrm{op}}+1$ BSs, each of which is owned by one operator. Thus, the BSs of the different operators are identically distributed and each operator controls N_{BS} of them. Although this is not generally the case, this assumption is used to simplify the problem.

3.1.1 Energy Consumption Model for Base Stations

We adopt the same power model given in (1) but we define $P_{n,j}^{(\mathrm{tx})}$, the radiated power of the j^{th} BS of mobile operator n, as a function of the number of users served by this BS, denoted by N_j, multiplied by a constant power and can be expressed as follows:

$$P_{n,j}^{(\mathrm{tx})} = P_{\mathrm{T}} N_j, \tag{16}$$

where P_{T} is a constant power and is defined such that

$$P_{\mathrm{T}} = \frac{P_{\min}}{K} R^{\upsilon}, \tag{17}$$

where $P_{\min}$ denotes the minimum received power required by each mobile station (i.e., it represents the user QoS), K is a parameter accounting for several effects including BS antenna settings, carrier frequency and propagation environment, υ is the path loss exponent, and R denotes the inter-cell distance. If a BS j is completely switched off, we assume that its power consumption $P_j = 0$.

3.1.2 CO_2 Emission Penalty Function

Recall that BSs are powered either from a traditional electricity provider or from renewable energy generators installed on BS sites. The consumption of fossil fuels causes a harmful impact on the environment due to the emission of GHGs. The amount of this damage depends on the nature of the energy source. The CO_2 emission penalty function of a network can be modeled as a quadratic function of the consumed fossil fuel by a BS as it is given in [22]:

$$\mathscr{I} = \sum_{j=1}^{N_{\mathrm{BS}}} \alpha_f \left(q_j^{(n,f)}\right)^2 + \beta_f q_j^{(n,f)}, \tag{18}$$

where α_f and β_f are the emission coefficients related to the energy source of the electricity provider.

3.2 Utility Functions and Problem Formulation

In our framework, we investigate the cooperation between the non-uniform mobile operators. We assume that one of them is considered as a green mobile operator. Its objective is to minimize its network CO_2 emissions, maximize its profit or achieve a tradeoff between both objectives. The other mobile operators, denoted by (NGO_n) $n = 1, \cdots, N_{\mathrm{op}}$, are considered as traditional mobile operators having the goal of the maximization of their own profit regardless of their impact on the environment. The NGOs cooperate with the GO by offloading its users when needed. For instance, GO might switch off some of its BSs during low traffic period and the corresponding subscribers can connect to the NGOs infrastructure. In return, NGOs may impose on the GO to pay extra charge per number of roamed users. Thus, the GO aims to determine the number of users per BS to be offloaded to the NGO networks in order to maximize its objective while the NGOs seek the optimal roaming prices to impose in order to attract GO users and maximize their profits. In the sequel, in order to differentiate between the GO and NGO parameters, the notation $x^{(\mathrm{GO})}$ and $x^{(\mathrm{NGO}_n)}$ will be used, respectively.

3.2.1 Green Operator

The first objective of the GO is to maximize its profit, $\mathscr{P}^{(\mathrm{GO})}$, expressed as

$$\mathscr{P}^{(\mathrm{GO})} = \sum_{j=1}^{N_{\mathrm{BS}}} p^{(\mathrm{GO})} N_{T,j}^{(\mathrm{GO})} - \sum_{l=1}^{N_{\mathrm{op}}} \pi_n^{(\mathrm{r})} N_{j,n}^{(\mathrm{r})} - \pi^{(\mathrm{GO})} q_j^{(\mathrm{GO},f)}, \tag{19}$$

where $p^{(\mathrm{GO})}$ denotes the service fee of the GO per user while $\pi_n^{(\mathrm{r})}$ corresponds to the roaming price per user imposed by the n^{th} NGO. $N_{T,j}^{(\mathrm{GO})}$ denotes the total number of GO users covered by BS j and $N_{j,n}^{(\mathrm{r})}$ is the number of users belonging to GO covered by BS j and served by NGO l. By definition, $q_j^{(\mathrm{GO},f)} = \max(P_j^{(\mathrm{GO})}\Delta t - q_j^{(\mathrm{GO},g)}, 0)$ where $P_j^{(\mathrm{GO})} = aP_{\mathrm{T}}N_j^{(\mathrm{GO})} + b$. Also, $N_{T,j}^{(\mathrm{GO})} = N_j^{(\mathrm{GO})} + \sum_{n=1}^{N_{\mathrm{op}}} N_{j,n}^{(\mathrm{r})}$, $\forall j = 1,\cdots,N_{\mathrm{BS}}$. However, if all users of BS j are roamed to neighbor BSs of other operators $N_{T,j}^{(\mathrm{GO})} = \sum_{n=1}^{N_{\mathrm{op}}} N_{j,n}^{(\mathrm{r})}$ (i.e., $N_j^{(\mathrm{GO})} = 0$), then the BS j is turned off and $P_j^{(\mathrm{GO})} = 0$, Finally, $\pi^{(\mathrm{GO})}$ is the unitary cost of fossil fuels per kWh paid by the GO. The GO's second objective is to reduce the CO_2 emissions, $\mathscr{I}^{(\mathrm{GO})}$, defined in (18). GO might target to achieve a tradeoff between both objectives. For this reason, we introduce a Pareto parameter, denoted by ω, in its utility function $\mathscr{U}^{(\mathrm{GO})}$ which will be maximized using the following optimization problem:

$$\max_{N_{j,n}^{(\mathrm{r})}} \mathscr{U}^{(\mathrm{GO})} = \omega\,\mathscr{P}^{(\mathrm{GO})} - (1-\omega)\,\mathscr{I}^{(\mathrm{GO})} \tag{20}$$

$$\text{subject to: } N_j^{(\mathrm{GO})} + \sum_{n=1}^{N_{\mathrm{op}}} N_{j,n}^{(\mathrm{r})} = N_{T,j}^{(\mathrm{GO})},\ \forall j = 1,\cdots,N_{\mathrm{BS}}, \tag{21}$$

$$0 \le N_{j,n}^{(\mathrm{r})} \le N_{T,j}^{(\mathrm{GO})},\ \forall j = 1,\cdots,N_{\mathrm{BS}}, \forall n = 1,\cdots,N_{\mathrm{op}}. \tag{22}$$

When $\omega \to 1$, we are dealing with the utility function given in (19). This corresponds to a selfish network operator that aims to maximize its own profit $\mathscr{P}^{(\mathrm{GO})}$ regardless of its impact on the environment. When $\omega \to 0$, we deal with the utility function given in (18), which corresponds to an environmentally friendly network operator that aims to reduce CO_2 emissions regardless of its own profit. Other values of ω constitute a tradeoff between these two extremes.

3.2.2 Non-Green Operators

On the other hand, each NGO n tries to maximize its profit by serving as many roamed users as possible. Its utility function $\mathscr{U}^{(\mathrm{NGO}_n)}$ can be optimized using an optimization problem formulated as follows

$$\max_{\pi_n^{(\mathrm{r})}} \mathscr{U}^{(\mathrm{NGO}_n)} = \sum_{j=1}^{N_{\mathrm{BS}}} p^{(\mathrm{NGO}_n)} N_j^{(\mathrm{NGO}_n)} + \pi_n^{(\mathrm{r})} N_{j,n}^{(\mathrm{r})} - \pi^{(\mathrm{NGO}_n)} q_j^{(\mathrm{NGO}_l,f)} \tag{23}$$

$$\text{subject to } \pi_n^{(\mathrm{r})} \ge a\pi^{(\mathrm{NGO}_n)} P_{\mathrm{T}} \Delta t, \tag{24}$$

where $q_j^{(\mathrm{NGO}_n,f)} = \left(aP_{\mathrm{T}}\left(N_j^{(\mathrm{NGO}_n)} + N_{j,n}^{(\mathrm{r})}\right) + b\right)\Delta t$. Note that constraint (24) was added to ensure that the NGOs will always choose a profitable roaming price. In other words, if serving GO users is not beneficial, then NGOs will prefer to not cooperate.

3.3 Analysis of the Stackelberg Equilibrium

In order to solve the problem formulated in Section 3.2, we propose to model it as a Stackelberg game where the GO plays the role of the follower and NGOs play the role of the leaders. We apply a backward induction approach to derive the solution of the Stackelberg Equilibrium.

3.3.1 Green Operator Level Game: The Follower

The objective of the follower is to determine how many users per BS are needed to be roamed for NGO l in order to maximize its utility function. As the leaders aim to maximize their utility functions anticipating the predicted response of the follower, we should start first by deriving the best response of the follower with respect to the numbers of roamed users per BS $N_{j,n}^{(\mathrm{r})}, \forall j = 1, \cdots, N_{\mathrm{BS}}, \forall n = 1, \cdots, L$. It is known that the problem solution is an integer solution; however, we propose to relax the problem by transforming the integers to real non-negative variables. Then, we round the obtained solution to find the exact number of roamed users. Thus, the number of roamed users to the l^{th} NGO can be obtained by computing the first derivative of the Lagrangian function with respect to $N_{j,n}^{(\mathrm{r})}$ and equating to zero. We showed in [21] that the second derivative of the utility function with respect to the number of roamed users is negative. Thus, $U^{(\mathrm{GO})}$ is concave with respect to $N_{j,n}^{(\mathrm{r})}$. Finally, the optimal number of roamed users per BS is expressed as follows

$$\begin{aligned} N_{j,n}^{(\mathrm{r})\,(*)} = \min\Bigg\{ \Bigg[& N_{T,j}^{(\mathrm{GO})} - \sum_{\substack{k=1 \\ k\neq l}}^{N_{\mathrm{op}}} N_{j,k}^{(\mathrm{r})} + \frac{b\Delta t - q_j}{aP_{\mathrm{T}}\Delta t} + \frac{\beta_f}{2\alpha_f aP_{\mathrm{T}}\Delta t} \\ & + \left(\frac{\omega}{1-\omega}\right)\frac{\pi^{(\mathrm{GO})}}{2\alpha_f aP_{\mathrm{T}}\Delta t} - \left(\frac{\omega}{1-\omega}\right)\frac{\pi_n^{(\mathrm{r})}}{2\alpha_f (aP_{\mathrm{T}}\Delta t)^2}\Bigg]^+, N_{T,j}^{(\mathrm{GO})}\Bigg\}, \end{aligned} \tag{25}$$

where $\min(.,N_{T,j}^{(\mathrm{GO})})$ and $[.]^+ = \max(.,0)$ are added to fulfill constraints (21) and (22), respectively. From the expression above, we can notice that the number of roamed users per BS decreases with the increase of the NGO roaming price. Moreover, we can see that this decrease depends on the GO's Pareto weight. For instance, when $\omega \to 1$, the GO is more and more concerned by its profit and thus the decrease of the number of roamed users is more important.

3.3.2 Non Green Operator Level Game: The Leader

The objective of the leader l in this Stackelberg game is to maximize its profit by attracting the maximum number of GO users. Therefore, the NGO l has to find the best roaming price depending on the system parameters in order to optimize its Stackelberg Equilibrium by injecting the relationship given in (25) in its utility function and deriving its first derivative with respect to the roamed price $\pi_n^{(\mathrm{r})}$ and equating it to zero. Hence, the optimal roaming price of NGO l is given as follows

$$\pi_n^{(\mathrm{r})(*)} = \max\left\{ \left(\frac{1-\omega}{\omega}\right) \left[\frac{\alpha_f (aP_{\mathrm{T}}\Delta t)^2}{N_{\mathrm{BS}}} \sum_{j=1}^{N_{\mathrm{BS}}} \left(N_{\mathrm{T},j} - \sum_{\substack{k=1\\k\neq l}}^{N_{\mathrm{op}}} N_{j,k}^{(\mathrm{r})} \right) + \alpha_f a P_{\mathrm{T}} \Delta t \left(b\Delta t - \sum_{j=1}^{N_{\mathrm{BS}}} \frac{q_j}{N_{\mathrm{BS}}} \right) + \frac{aP_{\mathrm{T}}\Delta t}{2} \beta_f \right] + \frac{aP_{\mathrm{T}}\Delta t}{2} \left(\pi^{(\mathrm{GO})} + \pi^{(\mathrm{NGO}_n)} \right), a\pi^{(\mathrm{NGO}_n)} P_{\mathrm{T}} \Delta t \right\}. \quad (26)$$

Note that the $\max\{.\,, a\pi^{(\mathrm{NGO}_n)} P_{\mathrm{T}} \Delta t\}$ is added to ensure that the profit of a leader will not decrease below its profit obtained without cooperation as it is given in constraint (24). $U^{(\mathrm{NGO}_n)}$ is also concave with respect to $\pi_n^{(\mathrm{r})}$ as its second derivative with respect to $\pi_n^{(\mathrm{r})}$ is also negative.

From expressions (25) and (26), it can be noticed that the determination of the SE of the n^{th} leader depends on the number of roamed users to the other $(N_{\mathrm{op}} - 1)$ NGOs as well as their respective roaming prices. Therefore, we propose to employ a fixed point algorithm to determine the optimal number of roamed users and the corresponding roaming prices.

4 Results and Discussion

In this section, we investigate the performance of the proposed approach for uniform mobile operator collaboration detailed in Section 2. Then, we discuss the results obtained for the non-uniform mobile operator collaboration setting.

4.1 Performance of the Collaboration between Uniform Mobile Operators

We consider $N_{\mathrm{op}} = 2$ mobile operators, denoted by A and B, serving a $5 \times 5\,(\mathrm{Km}^2)$ LTE coverage area. A and B are placing uniformly $N_{\mathrm{BS}}^{(1)} = 16$ and $N_{\mathrm{BS}}^{(2)} = 9$ BSs, respectively. We assume the nonexistence of inter-operator interference and both

Table 1: Service parameters

Services	Service 1	Service 2	Service 3
$p^{(m)}$(MU)	10	5	1
$(R_{m,th}^{(\mathrm{DL})}, R_{m,th}^{(\mathrm{UL})})$ (kbps)	$(1000,384)$	$(384,384)$	$(64,64)$
Occurrence Probability (%)	15	25	60

networks are operating in disjoint 10 (MHz) bandwidths that are subdivided into $N_{\mathrm{RB}} = 50$ RBs. The LTE and channel parameters are obtained from [19]. All BSs and all mobile stations have the same power model with the same maximal transmit power 46 dBm, $a = 21.45$ and $b = 354.44$ W. We set $\upsilon = 3.76$, $\kappa = -122.1$ dB, $\sigma_\xi = 8$ dB and the tolerance $P_{out} = 2\%$. The mobile station transmit power is set to 23 dBm. In addition, we suppose that the network operators offer similar $M = 3$ services. Each one is characterized by its cost (unitary price) $p^{(m)}$, expressed in monetary units (MU), DL and UL data rate thresholds ($R_{m,th}^{(\mathrm{DL})}$ and $R_{m,th}^{(\mathrm{UL})}$ respectively), and the occurrence probability of the service as it is shown in Table 1. The occurrence probability of a given service corresponds to the percentage of users in the network using that service.

Mobile operators are procuring energy either from electricity retailer, which provides enough energy to cover the network operation, or from renewable energy generated locally. We assume that amount of energy available at each BS varies between 0 and 100 Watt which corresponds to the maximum amount of energy that can be stored locally during the operation time $\Delta t = 1$ second. We set the unitary price of the fossil fuel to $\pi^{(f)} = 0.1$ (MU). Finally, we assume that $N_U^{(1)} = \alpha N_U^{(2)}, 0 \leq \alpha \leq 1$ and that mobile operators are engaged to serve 98% of the connected users simultaneously (i.e., $P_{\mathrm{out}} = 0.02$). In our results, we compare our approach, denoted by “coop”, with the traditional case, denoted by “uncoop”, when both cellular companies operate individually in addition to the case when all BSs are assumed to belong to a single virtual network operator, denoted by “virtual”.

In Table 2, we study the performance of mobile operator collaboration versus the number of subscribers connected to the networks for $\alpha = \frac{2}{3}$. In all scenarios, the amount of renewable energy generated by the BSs is the same. We notice that the proposed cooperative scheme achieves almost the same performance as the virtual scenario by activating almost the same number of BSs and consuming a slightly higher amount of fossil fuels. This small difference is due to the QoS constraints separately imposed on each operator as it is given in (10) while, in the virtual scenario, there is only one constraint as it is a single big network. Compared to the traditional case, an important energy saving is obtained thanks to cooperation. For instance, for $N_U^{(1)} = 130$, the fossil fuel consumption is reduced by more than 23%. Concerning the profit, we notice that the results satisfy the condition imposed in (12) that forces the cooperation profits to be higher than the individual ones by choosing an appropriate roaming price. For instance, the gained profit when collaborating is

Table 2: Approach performance versus total number of users ($\alpha = 2/3$)

Number of A users $N_U^{(1)}$	20	80	140
Uncoop. fossil fuels (kW) [Active BSs]	1.8[4.3]	5.1[10.7]	8.5[16]
Coop. fossil fuels (kW) [Active BSs]	1[2.7]	4[7]	6.9[11]
Virtual fossil fuels (kW) [Active BSs]	1[2.7]	3.7[6]	6.3[9.2]
Uncoop. profit (kMU): A, B	0.10, 0.06	0.98, 0.62	1.86, 1.21
Coop. profit (kMU): A, B	0.12, 0.08	1.04, 0.68	1.96, 1.30
Roaming price (MU)	5.37	2.84	1.19

greater by 5% than the uncooperative case for both operators when $N_U^{(1)} = 70$. This is because with collaboration, mobile operators are offered more degrees of freedom in order to reduce the energy cost and maximize their profit. To achieve this gain, an appropriate choice of roaming price has to be determined by solving (12). We can see that the higher traffic densities are, the lower the roaming price is. Finally, our simulation experiments indicate that the percentage of successful cooperation is 97%. In other words, the probability that mobile operators decide to not cooperate is $\approx 3\%$.

Fig. 2 investigates the impact of generating renewables by mobile operators on the cooperation performance for $N_U^{(1)} = 50$ and $\alpha = \frac{2}{3}$. To do this, we introduce a parameter β_{RE} that represents the percentage of green energy generated by A while $100 - \beta_{RE}$ corresponds to the percentage of green energy generated by B. In other words, if $\beta_{RE} = 0\%$, then only B possesses renewables and vice versa. We assume here that all BSs owned by an operator are storing the same amount of renewables. In Fig. 2(a), we plot the consumed fossil fuels. We notice that the operator that is controlling renewable energy is able to reduce its CO_2 emissions more when there is no cooperation with a gain in terms of profit (Fig. 2(b)). However, when cooperating, most of its BSs are kept active to serve most of the users of the competing provider (as it is shown in Fig. 3(a), 90% and 95% for $\alpha = \frac{2}{3}$ and $\alpha = \frac{1}{3}$, respectively). However, the optimal value is when $\beta_{RE} = 50\%$. At this equilibrium, all BSs of both operators have the same characteristics and thus the BS selection set is larger. The curves are unbalanced because of the difference in the number of connected users and the number of available BSs per each operator. Finally, we can notice that the roaming price is higher when A is controlling the renewable energy. Indeed, as the number of subscribers of B is lower, A is forced to increase the roaming price in order to maximize its profit when cooperating, while the inverse can be deduced for B. Note that in all our simulations, the network QoS is satisfied for all operators, i.e., $P_{\text{out}} = 2\%$.

It is inpractical to assume that the roaming price varies instantaneously and dynamically with each channel in the network. It should have a pre-defined fixed average value for a given traffic density, or range of traffic densities in the network (e.g., there can be a price during the day corresponding to high density and another during the night corresponding to relatively lower density). This value can be set through collaboration agreements between mobile operators. The results derived in

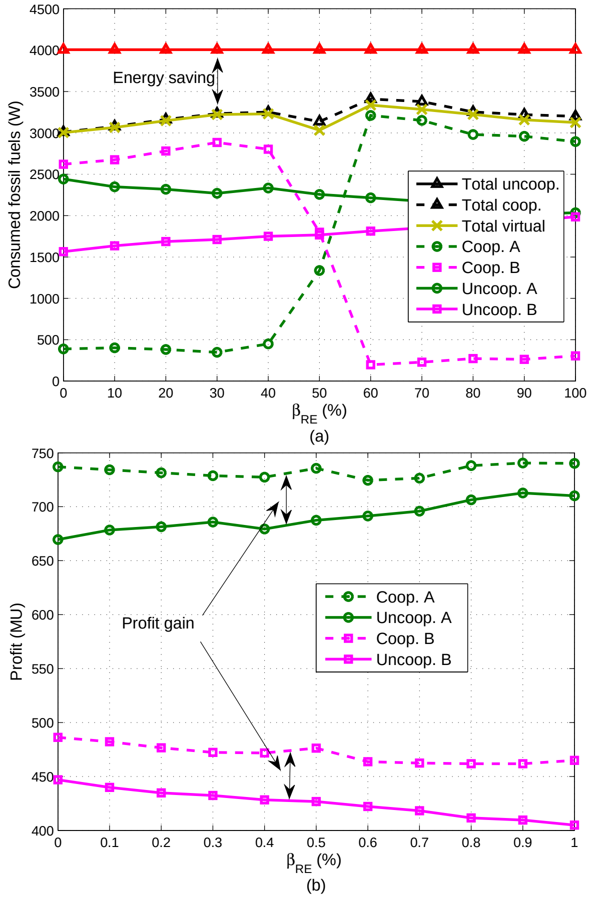

Fig. 2: (a) Consumed fossil fuels (b) Profit of mobile operators versus the distribution of green energy over cellular networks β_{RE}.

these simulations are averaged over 1000 channel realizations using Monte Carlo simulations. Hence, these results provide insights about the average roaming price that should be imposed between mobile operators for different traffic densities in order to ensure mutual benefit.

4.2 Performance of the Collaboration between Non-Uniform Mobile Operators

In this section, we present some numerical results for one-follower one-leader setting and one-follower two-leaders setting as an example of the scheme proposed in Section 3. We consider an area of interest where the $N_{\mathrm{op}}+1$ mobile operators are deploying $N_{\mathrm{BS}}=10$ identical BSs. All the BSs are powered by traditional electricity providers except the BSs of the GO network which are also supplied via green energy equipment deployed in BS sites. The amount of the auto-generated green energy differs form a BS to another. This can be explained essentially by the fact that

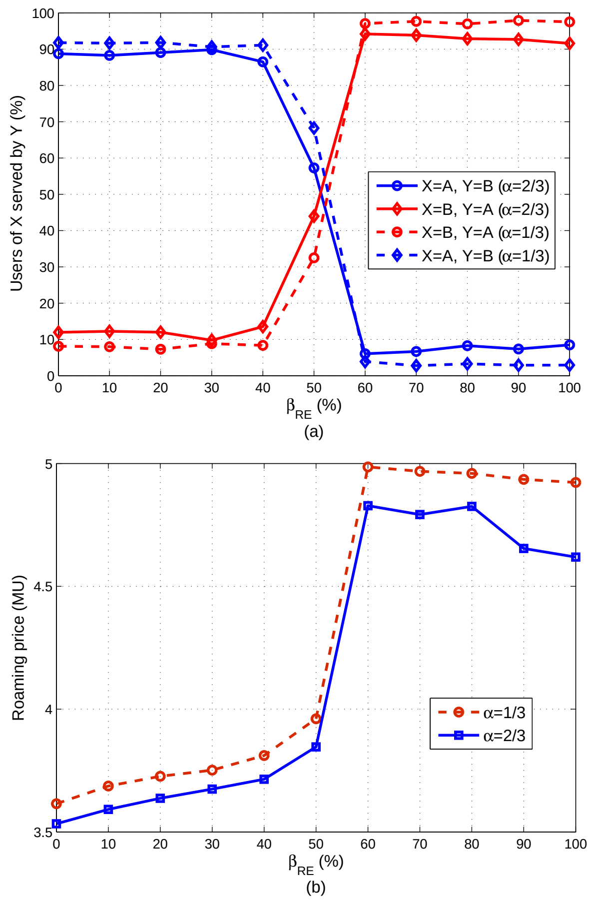

Fig. 3: (a) Users of mobile operator x served by mobile operator y (b) roaming price versus the distribution of green energy over cellular networks β_{RE}.

PV panels in BS sites have different sizes and whether they experience any shading during the day. Finally, we consider that $p^{(\mathrm{GO})} = p^{(\mathrm{NGO}_n)} = 5\,\mathrm{MU}, \forall n = 1, \cdots, N_{\mathrm{op}}$ (MU stands for monetary unit). In our simulations, we set the channel and power parameters as it is detailed in Table 3.

First, we investigate the one-leader one-follower scenario where only one NGO is available to serve the users of the GO. In Table 4, we study the cooperation between the operators for three cases when $\pi^{(\mathrm{GO})} = 0.2 < \pi^{(\mathrm{NGO})} = 0.4$ and $\pi^{(\mathrm{GO})} > \pi^{(\mathrm{NGO})} = 0.4$. For each case, we vary the Pareto weight ω representing the behavior of the GO towards the environment and we provide some information about the number of roamed users and the NGO roaming price. The amount of energy $q_j^{(\mathrm{GO})}$ available in each GO's BS and the number of users served by each BS $N_{T,j}^{(\mathrm{GO})}$ are also given in Table 4. We assume that $N_{T,j}^{(\mathrm{GO})} = N_{T,j}^{(\mathrm{NGO})}$. We can first deduce that there are three categories of BSs in this roaming setting. BSs that offload all their users to the NGO (e.g., $j = 2, 6, 8$): These BSs, having very low amounts of renewable energy, prefer to be turned off instead of serving users using fossil fuel independently of the value of $\pi^{(\mathrm{GO})}$. The second category is the BSs that do not offload any users as they have sufficient amount of green energy to serve all of them (e.g., $j = 4, 9, 10$). The final category encloses the BSs that offload some of their users depending on the available amount of green energy (e.g., $j = 1, 3, 5, 7$). Another remark is that as ω increases the roaming price $\pi^{(r)}$ decreases. Indeed, as it is more concerned by its profit, the GO tries to avoid the maximum to pay extra roaming fees. Thus, NGO are obliged to reduce their roaming price to attract GO users. We can see that the higher $\pi^{(\mathrm{GO})}$ is, the higher $\pi^{(\mathrm{r})}$ is.

Let us now study the cooperation behavior case by case. When $\pi^{(\mathrm{GO})} < \pi^{(\mathrm{NGO})}$, we notice that as ω increases the number of roamed users decreases. In the case, $\omega = 0.1$, GO offloads the maximum number of users such that it minimizes its CO_2 emissions. This means that most of GO users are either served by green energy or by NGO infrastructure. When ω is close to 1, we can see that GO does no more offload users since it prefers to serve them using its BSs even with fossil fuels as its $\pi^{(\mathrm{GO})} < \pi^{(\mathrm{NGO})}$. Now, if $\pi^{(\mathrm{GO})} > \pi^{(\mathrm{NGO})}$, we can see as ω increases, the number of roamed users increases too. In this case, the GO prefers to offload its users as its fossil fuel cost is more expensive than the NGO one and is more and more concerned by its profit.

In Fig. 4, we investigate the performance of the proposed scheme for one follower and two leaders scenario. In this case, we set $\omega = 0.6$ which belongs to the

Table 3: System parameters

Parameter	**Value**	**Parameter**	**Value**
$P_{\min}$	-120 dBm	υ	3.76
K	0.0001	R	1000 m
(a,b)	$(7.84, 71.5)$	(α_f, β_f)	$(0.02, 0.1)$

Table 4: Performance of the proposed scheme for one NGO one GO case

			$\pi^{(\mathrm{GO})} = 0.2 < \pi^{(\mathrm{NGO})} = 0.4$					$\pi^{(\mathrm{GO})} = 0.6 > \pi^{(\mathrm{NGO})} = 0.4$				
ω			0.1	0.4	0.6	0.9	0.98	0.1	0.4	0.6	0.9	0.98
$\pi^{(\mathrm{r})}$(MU)			10.53	2.03	1.08	0.45	0.44	10.75	2.25	1.30	0.67	0.57
j	$q_j^{(\mathrm{GO,g})}$	$N_{T,j}^{(\mathrm{GO})}$	$N_j^{(\mathrm{r})}$					$N_j^{(\mathrm{r})}$				
1	90	47	9	8	6	0	0	9	11	13	30	47
2	9	21	21	21	21	21	0	21	21	21	21	21
3	74	65	41	40	38	21	0	42	43	45	62	65
4	145	49	0	0	0	0	0	0	0	0	0	49
5	71	51	30	29	27	10	0	31	32	34	51	51
6	4	39	39	39	39	39	0	39	39	39	39	39
7	57	80	72	71	69	52	0	72	74	76	80	80
8	13	59	59	59	59	59	0	59	59	59	59	59
9	105	17	0	0	0	0	0	0	0	0	0	17
10	208	71	0	0	0	0	0	0	0	0	0	37
Total	776	499	271	267	259	202	0	273	279	287	342	465
$\mathscr{P}^{(\mathrm{GO})}$			-379.5	1932	2192	2368	2378	-497	1815	2073	2262	2227
$\mathscr{I}^{(\mathrm{GO})}$			53.9	58.6	68.6	164.6	1147	51.7	45.1	37.1	0.12	0
$\mathscr{U}^{(\mathrm{NGO})}$			4725	2413	2156	1992	1988	4805	2494	2237	2069	2050

Pareto efficiency region as it is given in Table 4 and we set $\pi^{(\mathrm{GO})} = 1.5$ (MU) and $\pi^{(\mathrm{NGO}_2)} = 1$ (MU). Finally, we vary $\pi^{(\mathrm{NGO}_1)}$ between 0 and 2 (MU). In Fig. 4(a), we investigate the performance of all operators under the proposed cooperation mode (denoted by Prop.) when varying the fossil fuel cost of NGO 1 by plotting their utilities functions. Also, we compare them with the performance of the non-cooperation mode (denoted by Trad.) where all operators serve their own users without roaming. The figure shows that, thanks to their collaboration, all operators are able to enhance their performance comparing to the traditional scenario. Indeed, independently of the value of $\pi^{(\mathrm{NGO}_1)}$, GO is able to double its utility function while NGO utilities vary according to the NGO 1 fossil fuel cost. Indeed, as $\pi^{(\mathrm{NGO}_1)}$ increases, $U^{(\mathrm{NGO}_1)}$ decreases until coinciding with the traditional case, while $U^{(\mathrm{NGO}_2)}$ increases with a lower scale. NGO 2 exploits the high cost that NGO 1 is facing to provide a lower roaming user price and thus attract more GO users as it is shown in Fig. 4(b) and Fig. 4(c) where we plot the roaming prices and number of users, respectively. From these figures, we can see that when NGO 1 cost is low, both roaming prices are low and NGO 1 is gaining most of the roamed users (about 260 users) while NGO 2 is serving about 95 GO users. As $\pi^{(\mathrm{NGO}_1)}$ increases, NGO 1 is loosing roamed users while NGO 2 is serving more even if they provide the same roaming price. This is due to the fact that NGO 1 is obliged to increase its roaming price to face the energy price increase and NGO 2 exploits this to also increase its roaming price knowing that GO is interested in reducing its CO_2. However, we notice that GO is more interested in serving its users as the roaming price is becoming more and more expensive.

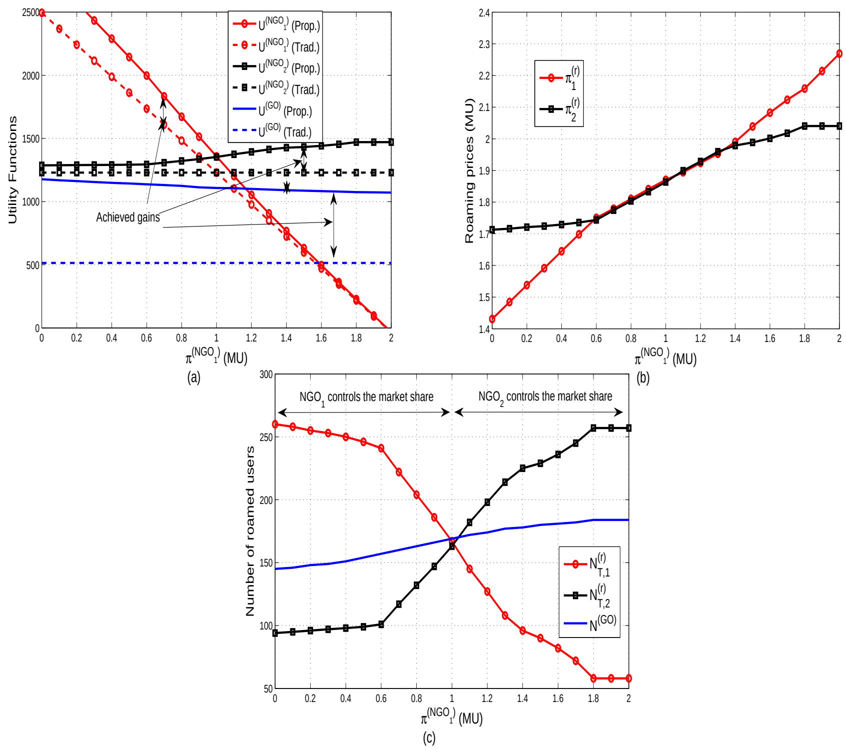

Fig. 4: Performance of the proposed scheme for one GO two NGOs versus $\pi^{(\mathrm{NGO}_1)}$ (a) utility functions (b) NGO roaming prices and (c) number of users (roamed $N_{T,n}^{(r)}$, not roamed $N^{(GO)}$).

4.3 Insights from the Results and Future Challenges

The results show that cooperation between multiple operators can be beneficial, and it could lead to a win-win situation for all parties. Operators can increase their revenues from roamed subscribers, while cutting their operating costs by reducing significantly their energy consumption. The selection of suitable roaming prices will allow the serving operator to generate revenue from the roamed users, whereas the original operator offloading its subscribers will be able to save energy costs by switching off redundant BSs. In addition, the whole cooperation process is environmentally friendly since it leads to reduced CO_2 emissions, while respecting users QoS and maintaining, even increasing, the operators profits. Throughout the operation of the network, the roles of the operators will be reversed, depending on the network dynamics. Hence, each operator will at certain times (or at different locations, at the same time) save energy by switching off some of its BSs, while at other times (and/or locations), it will be serving the roamed users of other operators.

In practice, this multi-operator collaboration is in line with the active research area of network function virtualization (NFV) and service orchestration. In fact, mobile virtual network operators (MVNOs) are a market reality, where a physical operator lends its infrastructure (e.g., the mobile access network) to be used by several other virtual operators. Having two existing operators unite the operation of their networks for the benefit of all can thus be implemented in practice. However, the main challenge is in pricing and billing issues. Operators need to find the best roaming price that can lead to benefits for all involved parties. This requires an assessment of the value of the savings obtained by switching a certain BS off and of the costs incurred by the new serving operator to serve subscribers of other operators. Once studies are made to estimate these values, suitable billing agreements can be signed between concerned operators. The whole process remains transparent to subscribers, who will pay their bills to their initial operator, and will receive their expected QoS seamlessly across the networks of the collaborating operators.

5 Summary

In this chapter, we investigated the performance of the green networking approach for multi-operator collaboration for two different settings: The uniform mobile operator collaboration and the non-uniform mobile operator collaboration. In the first scenario, we have formulated an optimization problem that aims to reduce the total CO_2 emissions by eliminating redundant base stations while respecting the network QoS. We have also derived a system of linear inequalities to decide whether to cooperate or not by determining the roaming price. Our approach leads to an important saving in terms of fossil fuel consumption while it enhances the cooperative mobile operator profit. In addition, it shows that the roaming price is inversely proportional to the number of subscribers of the network as well as the number of BSs generating renewables.

In this second scenario, we investigated the performance of a green networking system where one green operator interested in minimizing its CO_2 emissions cooperates with several non green operators interested in maximizing their own profits by serving the green operator subscribers. The problem was formulated as a two-level Stackelberg game that leads to the maximization of both player utility functions. A Stackelberg equilibrium was derived and the optimal roaming prices and number of offloaded users are determined. Our simulation results showed the behavior of each mobile operator in this competition game and showed that the green operator is able to ensure a significant reduction in terms of CO_2 emissions compared to the traditional case.

At the moment, collaboration between mobile companies are still not applied in reality. Therefore, there is a pressing need to propose additional and new approaches in order to encourage telecommunication leaders and regulators to discuss and focus more on such approaches for possible implementation in next cellular network generation. The work can be extended and enriched by formulating differently the problem. Game theoretical approaches could be used to model the coalition and/or the competition among mobile operators while including the dynamic traffic variation.

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