Greening the Airwaves With Collaborating Mobile Network Operators

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***Abstract*—Base station sharing is currently considered one of the most promising solutions for reducing the energy consumption costs of cellular networks. This paper presents a game theoretic framework for the study of such cooperative solutions where different mobile network operators (MNOs) decide to switch OFF subsets of their base stations during off-peak hours and roam their traffic to the remaining stations. The solution is based on a detailed optimization framework that determines exactly which base stations should remain active and how much traffic each one of them should serve, so as to maximize the aggregate energy savings. Accordingly, using the axiomatic Shapley value rule, it is determined how the benefits from the cooperation, i.e., the cost savings, should be dispersed among the cooperating MNOs. It is proved that this coalitional game with transferrable utilities has a nonempty core, and thus there exists a cooperation solution that incentivizes the participation of all operators. Moreover, using a thorough numerical analysis, it is shown that the benefits achieved with the implementation of the cooperation strategy depend mainly on the power consumption characteristics of the MNOs, which in turn are related to the number, type, and technology of their base stations. Overall, the energy savings are found to be most sensitive to the technology of the used base stations, and more precisely to the no-load base station energy consumption which defines the energy waste in a network.**

***Index Terms*—Base station management, coalitional games, energy efficient networking, game theory, mobile network operators, wireless networks.**

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I. Introduction

A. Background and Motivation

According to the widely accepted recent forecasts by Cisco and Ericsson, mobile data is expected to increase with an annual growth rate of 60% in the next five years, reaching 25 Exabytes per month in 2020 [1], [2]. This explosive traffic growth places unprecedented strain on mobile network operators (MNOs), increases their operating and capital expenditures, and even challenges their economic viability. Today it is commonly agreed that one of the most critical cost factors for cellular networks is the energy consumption of their active network components [3], [4]. Up to 90% of this cost is realized at the Radio Access Network (RAN), and, specifically, it is induced by the power consumption of base stations (BSs). Indeed, a conventional macro BS (MBS) exhibits high power consumption ranging from 800 W to 2 kW (older models reached up to 3.5 kW), while a micro BS (mBS) requires 300 W even when it does not serve any traffic [5]. This creates on average an annual consumption of 15 MWh and 2 MWh, respectively. Therefore, a MNO with 5000 MBSs and 5000 mBSs has operating expenses (electricity) of the order of \$8 million per year.

A large body of academic studies and industry activities [6], [7], [8] have recently focused on identifying effective approaches that will allow MNOs to reduce these energy costs. One of the first proposed methods were energy-prudent management techniques which switch off some base stations, putting them into a *sleep mode*, when the traffic in their area is relatively low and thus can be transferred to neighboring base stations (*intra-network sharing*). The key motivation for such sharing methods are that (i) cellular traffic follows mostly a periodic pattern[1] while the network capacity is dimensioned based on the peak traffic value, and (ii) in many cases the base stations coverage areas overlap so that it is possible to use only a subset of them in off-peak hours. An even more radical solution is the cooperation among different MNOs so as to share their whole RAN infrastructure in some geographic area (*inter-network sharing* or MNO cooperation).

The main idea in this latter approach is to switch off at once multiple base stations of a MNO in a certain area, and serve its

[1]Typical reasons for the diurnal patterns of the MNO traffic are the day-night user behavior, and the spatial variation because of the migration of mobile users among different areas.

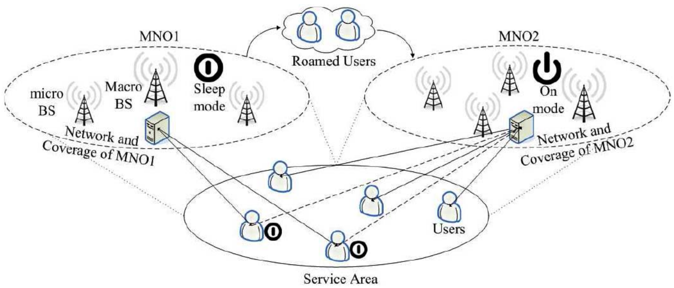

Fig. 1. A set of MNOs, owning and managing different radio access network (RAN) infrastructures, provide service to a common area. Each MNO can decide to *switch off* its RAN for a certain time period and roam its traffic to another MNO. The process is transparent for the end-users.

users by roaming their traffic to other MNOs that provide coverage in the same area. This idea is currently gaining increasing research interest and has been already adopted by several operators, e.g., see [9], which exploit the fact that often their BSs are very closely located or even co-located (*mast sharing*). Unlike with the intra-network sharing approach, in this case each MNO is not required to have overlapping BSs (over-provisioning) since the BSs of the remaining operators can directly serve the roaming traffic without having to increase their transmission power or adjust their antennas. In general, this approach offers a larger set of solutions with possibly higher benefits [10] especially when the networks are not always congested (varying traffic load), and the MNOs are diverse in terms of the deployment of their base stations.

However, inter-network sharing schemes bring new challenges as the MNOs need to coordinate and agree on several issues. In particular, they need to jointly devise the BSs switching on/off policy that will reduce the total energy servicing cost (i.e., across all MNOs), and agree on how to roam the traffic of the operators that will switch off their infrastructure to those that will remain active. Additionally, the MNOs should reach consensus on the prices that will be charged for the roaming services. Clearly, operators serving additional traffic will be interested in asking higher compensations, while operators that switch off their networks would prefer to be charged as low as possible for this service. In areas with more than two MNOs multiple cooperation choices exist, and thus it is challenging (i) to identify the optimal solution in terms of aggregate energy saving for all operators, and (ii) to devise the charging policy that can provide adequate incentives for the cooperation of all the involved MNOs. Addressing these issues is of paramount importance for the adoption of these innovative network sharing strategies, which can create revenues of the order of million dollars per year.

B. Related Works and Contributions

The general scenario for RAN sharing schemes is depicted in Figure 1. A macroscopic view of the inter-network RAN sharing problem was first introduced in [10] and [11] which explored potential sharing strategies and studied the expected energy savings. In particular, for the largest European countries it was estimated [10] that the energy costs can be reduced by 35% to 58%. A microeconomic analysis based on a non-cooperative game theoretic model for the scenario where two MNOs share their BSs in a single cell is presented in [12]. The authors characterized the *Nash Equilibria* and explored their dependency on key parameters such as the network capacity of each MNO, the respective traffic load, and the roaming fees. Similarly, in [13] the authors considered a non-cooperative game with limited information about each operator's traffic, and studied the respective Bayesian equilibria. Another interesting suggestion is to allow MNOs to share different resources, e.g., exchanging energy surpluses with idle spectrum, as it was proposed in [14], [15].

The above scenarios build upon the initial intra-network sharing schemes where each MNO activates only a subset of its own base stations whenever traffic is relatively low in a certain area. In this case, the main challenge is to find the optimal on/off switch pattern by solving the proper optimization problem. The goal is to minimize the MNO's energy consumption, while satisfying the minimum quality of service (QoS) and spatial coverage constraints, e.g., see [16], [17] and the references therein. The most commonly used on/off switch management techniques can be classified as centralized, distributed and pseudo-distributed (hybrid). The practical implementation of these schemes can be achieved through static or dynamic management, as described in [16]. These BS management approaches enhance network functionalities such as self-organization, self-healing and self-optimization within the network of each operator and, interestingly, up to a certain extent are already supported by industrial standards [20].

In this work we study inter-network sharing, and we adopt a more general approach where multiple MNOs take decisions to share their base stations in a given region. That is, we assume that each operator decides for the entire set of its BSs (i.e., for its RAN) in that area at once. More detailed approaches, i.e., per BS, would increase the number of required handovers for users, which in turn has important energy (and often also performance) costs for mobile devices [21]. Moreover, sharing policies with such high granularity induce heavy overhead for MNOs which need to take different decisions per BS and every small subset of users.

We adopt a macroscopic approach and consider the average traffic that needs to be served in the area of interest by each operator, over a given time period. When each MNO acts independently, this traffic is split among its BSs based on a certain rule such as the maximum signal-to-noise (SNR) association criterion. We assume that operators have the same minimum QoS and coverage criteria. In other words, we do not consider traffic routing within the domain of each MNO, which is an orthogonal problem to our study. Regarding the average energy costs of the BSs, in line with previous findings [3], [4], [25], we approximate them with linear functions of the transmitted power, or, under the assumption of homogeneous traffic, of linear functions of the number of served users.

We formulate a detailed optimization problem in order to find the switching on/off policy, and determine the roaming policy for the traffic of those MNOs that set their BSs in sleep mode. This problem essentially falls into the broad class of facility location problems where each facility represents the BSs of a MNO [22]. These are well-known hard problems. However, inter-network sharing policies are devised over long time scales, e.g., for several days or even weeks, based on the traffic periodicity and traffic statistics, and hence can be solved offline with standard methods such as branch-and-bound [23]. Besides, we also propose a fast greedy algorithm that has been introduced for solving the single-demand-node capacitated facility location (SNCFL) problem [24], and, under mild conditions yields an optimal solution.

Unlike most previous works, we model the strategic interactions of the operators as a coalitional game with transferrable utilities (TU) [26], [28], since money transfers are possible among the different players (i.e., the MNOs). This approach allows us to investigate if all the MNOs will cooperate with each other by forming a single coalition, or if different sub-coalitions will emerge. Note that coalitional games have a more subtle premise than the non-cooperative ones, allowing the possibility that players negotiate so as to reach an efficient equilibrium. Clearly, assuming that MNOs compete fiercely without any coordination (as in non-cooperative games) is a strong assumption for this problem but can be used as a benchmark scenario [3]. On the other hand, a coalitional game was considered in [27] where stochastic geometry was employed to optimize the density of switched on BSs. In this case, the cooperation of the BSs aims to improve the SINR for each user (and hence reduce the total energy consumption), while the diurnal traffic pattern is not taken into account.

We prove that this game has a non-empty core and hence the grand coalition is stable [29]. Moreover, under the assumptions about the servicing cost functions of the MNOs, and for the macroscopic point-of-view that we adopt, we show that the Shapley values can be used to disperse in a fair fashion the cost reduction benefits among the cooperating operators [30]. This is an additional refinement method for selecting, among the multiple equilibria that may lie in the core, the one that is fair according to the axiomatic criteria introduced by L. Shapley. To this end, the main technical contributions of this work can be summarized as follows:

1. We employ a detailed model for the energy consumption costs of the operators, where we correlate the energy consumption of a BS with the number of the users it serves.

2. We provide a generic formulation for the MNOs' aggregate energy cost minimization problem. The solution of this problem yields the switching on/off policy, and the traffic roaming policy for the MNOs that have to set their BSs into sleep mode. The presented methodology constitutes a framework that can also be applied for different setups, e.g., when the energy consumption prices are time-varying or even load-dependent.

3. We introduce and solve the inter-network sharing coalitional game. We prove that the game has a non-empty core, and that it is convex. Hence, it is possible to employ the Shapley values and refine the equilibrium selection by imposing this additional fairness criterion.

4. We provide an extensive simulation analysis for various scenarios, and showing how the equilibria depend on key system parameters, such as the number of cooperating MNOs, the traffic, and the diversity of their network deployments.

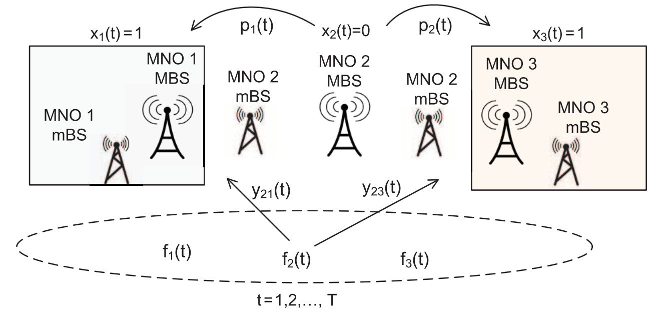

Fig. 2. An example with three MNOs that serve the same area. Operators MNO 1 and MNO 3 are active in the specific slot t, i.e., $x_1(t) = x_3(t) = 1$, while operator MNO 2 is switched off ($x_2(t) = 0$). The traffic of the latter is allocated to the two other MNOs as it is determined by the decision variables $y_{21}(t)$ and $y_{23}(t)$. Also, MNO 2 needs to reimburse MNOs 1 and 3 for their roaming services, by paying $p_1(t)$ and $p_2(t)$, respectively.

The paper is organized as follows. Section II introduces the detailed system model and the problem statement. Section III provides a definition of the coalitional game and the characterization of the respective equilibria, including the Shapley values. In Section IV we provide the numerical results that complement our analysis. Finally, we conclude in Section V.

II. System Model and Problem Statement

A. System Model

1) RAN and Traffic Model: We consider a geographical area $\mathbb{A}[km^2]$ that is covered by a set $\mathcal{J}$ of $|\mathcal{J}| \geq 2$ MNOs. The operators offer services of similar quality[2] (QoS) but may have different network planning strategies. The latter comprises decisions related to the deployment of BSs, such as their number, location, and their characteristics (antenna pattern, RF transmission power, etc.). We assume heterogeneous cellular architectures with different types of BSs, such as macrocell and microcell BSs. Namely, each MNO $i \in \mathcal{J}$ has a set $\mathcal{M}_i = \{1, 2, \ldots, M_i\}$ of macrocellular BSs (MBSs), and a set $\mathcal{K}_i = \{1, 2, \ldots, K_i\}$ of microcellular BSs (mBSs). We denote with $\mathcal{N}_i = \mathcal{K}_i \cup \mathcal{M}_i$ the set of all BSs that are managed by operator $i \in \mathcal{J}$. Different operators have, in general, different BS deployment strategies, hence it can be $|\mathcal{M}_i| \neq |\mathcal{M}_j|$ and $|\mathcal{K}_i| \neq |\mathcal{K}_j|$, $\forall i, j \in \mathcal{J}, i \neq j$. The general description of the system model and its parameters is depicted in Figure 2.

The planning of the MNOs is based on peak traffic conditions. We denote with CO_n the coverage area (set of grid points in the area) of BS $n \in \mathcal{N}_i$ of operator $i \in \mathcal{J}$. The BSs may have overlapping areas, but each user is associated to only one base station according to a best-server criterion (e.g., highest SNR rule). We assume that each MNO i has a subset of BSs $CB_i \subseteq N_i$ that guarantee the coverage of area $\mathbb{A}$. The BSs belonging to CB_i are called *critical stations* and are usually MBSs, responsible to provide coverage. The remaining stations $FB_i \subset N_i$, with $FB_i \cup CB_i = N_i$, are called *flexible stations*.

[2]The analysis can be extended for scenarios where different operators offer different QoS to their users, by properly modifying the cost functions. Namely, the higher is the QoS level (for a given user and location) the larger are the network resources (spectrum and/or power) that must be consumed per user in order to support it.

These can be MBSs or mBSs and are employed to satisfy the necessary capacity requirements. Flexible stations can be set in sleep mode when BS management schemes are implemented by a single MNO during low traffic periods. Clearly, whether a BS is flexible or critical depends on the network deployment strategy of the MNO (signal coverage) and the traffic demand (capacity coverage). In the analysis here we consider the type of each BS as given. Moreover, for the purpose of inter-network sharing, all BSs can be considered flexible since the access network of a MNO in a specific area can be entirely switched off during cooperation. In other words, inter-network sharing does not require that each MNO has overlapping BSs. Coverage and capacity in the service area is supported by the access network of other MNOs that remain active.

Every MNO $i \in \mathcal{J}$ at time $t = 1, 2, \ldots, T$ which is slotted, has a set $\mathcal{U}_i(t)$ of $U_i(t) = |\mathcal{U}_i(t)|$ active users (or subscribers) on average, that globally generate an aggregate traffic $f_i(t)$ (in bps), with $t \in [0, T]$ spanning over $T = 24$ hours. We define the vector:

$$\boldsymbol{f}_i = (f_i(t) : t = 1, \ldots, T)\,,\ i \in \mathcal{J}\,. \tag{1}$$

This traffic follows a periodic pattern: it is high in certain peak hours and much lower during night or other time-windows within the day [5]. Note that we adopt a macroscopic point of view and study average traffic $\beta > 0$ per end-user, i.e., $f_i(t) = \beta U_i(t)$, $i \in \mathcal{J}$, $t = 1, \ldots, T$, while we assume that the expected number of users for each MNO is known in advance based on collected statistics. In other words, due to the time-scale of the problem we rely on expected averages[3]. Finally, we denote with $f_i^n(t)$ the traffic of operator i that is served by its base station $n \in \mathcal{N}_i$. This is the traffic generated at time t by users $U_i^n(t)$ that are in range with BS n (belong in CO_n) according to a certain rule $L_i(\cdot)$ such as the max-SNR criterion [21]:

$$L_i\,(f_i(t)) : \mathbb{R} \to \mathbb{R}^{N_i}\,,\ \text{with} \sum_{n=1}^{N_i} f_i^n(t) = f_i(t)\,. \tag{2}$$

We denote by $J_i(\boldsymbol{f}_i)$ the servicing cost incurred by operator $i \in \mathcal{J}$ when it serves traffic during the time period T. In general, the servicing cost may vary with time (e.g., due to variation of the energy prices), and thus it can be written:

$$J_i(\boldsymbol{f}_i) = \sum_{t=1}^{T} J_i^t(f_i(t)) \tag{3}$$

where $J_i^t(\cdot)$ is the servicing cost per time slot. Here, we focus on energy costs. Namely, the operation of a BS is associated to electricity costs that are related to power consumption. Therefore, the monetary servicing cost, during each slot, can be written[4]:

$$J_i^t(f_i(t)) = q^t \cdot \sum_{n=1}^{N_i} C_n(U_i^n(t))\,, \tag{4}$$

[3]Clearly, such cooperation agreements can only be designed for relatively long-time periods, based on estimations of the operators for the peak traffic that they will need to serve. In practice, the roamed traffic can be less than expected, and then the charged fees will be reduced accordingly.

[4]Without loss of generality we assume that each slot has unit duration.

where q^t is the cost per unit of consumed energy that in general can change with t, and $C_n(\cdot)$ is the function that yields the energy consumption (in kWatts) for the users that BS $n \in \mathcal{N}_i$ serves. Please note that because the roaming decisions are taken in practice per users, we modeled the energy cost with respect to their numbers. Specifically, as we will explain in detail below, this quantity depends on the type and the load of the BS and can be written, $\forall n \in \mathcal{N}$, $t = 1, 2, \ldots, T$:

$$C_n(U_i^n(t)) = \begin{cases} a_n \cdot U_i^n(t) + b_n,\ BS\ is\ on \\ 0,\ BS\ is\ off \end{cases} \tag{5}$$

Equation (5) is an empirical one and is derived according to the methodology described in the sequel. We assume that if the BS is set in sleep mode (is off) then the power consumption is zero. In practice, sleep modes refer to negligible consumption compared to active mode. Parameter a_n is a multiplication factor that depends on the type of BS. It is expressed in Watts per user and it is computed in the sequel to be in the order of $a_n = 3$ if $n \in \mathcal{M}_i$ and $a_n = 0.7$ if $n \in \mathcal{K}_i$. Meanwhile, parameter b_n is expressed in Watts and describes the no-load (i.e., redundant) power consumption that characterizes the operation of cooling units and power units in the BS. We assume $b_n = 450$ if $n \in \mathcal{M}_i$, and $b_n = 32$ if $n \in \mathcal{K}_i$, according to [31], [32], [33], and [34].

2) Power Consumption Model: The consumption characteristic of the BSs may differ according to the used technology. For example, The Code of Conduct on Energy Consumption of Broadband Equipment of the European Commission JRC [18] mandates that 3G macro BSs (3 sectors, 2.1 GHz, 2 carriers per sector, with remote radio unit) released in 2016 should consume no more than 760 W at full load, and no more than 540 W at low load. In the case of LTE macro BSs (3 sectors, 2.6 GHz, 20 MHz, 2 × 2 MIMO) released in 2016, power consumption should be lower than 840 W at full load, and lower than 600 W at low load. Estimates of LTE macro BS power consumption in 2020 have been computed [19] in the framework of GreenTouch [8], obtaining values 700 W - 750 W at full load (2 × 2, 4 × 4 MIMO), and 120 W - 140 W at low load. Interestingly, in the latter study it was estimated that the times necessary to enter and exit sleep modes in which the power consumption is below 10 W are extremely short, i.e., of the order of 10 ms. For additional technical information we refer the interested reader to [5].

In more details, the power consumption is a function of the load of the BS. In the literature it is usually referred as a linear function of the transmitted RF power of the antenna, e.g., see [4]. In general, the RF out power is computed according to the radio technology used. In UMTS networks, perfect Signal to Interference Noise Ratio (SINR) based power control is used to allocate the resources (power in that case) to each user and satisfy the demand [35]. In LTE networks, the power allocation is performed for each resource block and the aggregated power represents the power assigned to the user. The number of blocks is related to the requested user service. For the purpose of our investigation, we have expressed the power consumption of the BS as a function of the number of served users. In that way, the equation used to express power can significantly simplify simulation results for the computation of the network power consumption. Besides, the roaming decisions are taken in practice on a per-user basis. To achieve this, we have performed simulations that capture a great diversity of randomly generated scenarios.

Let us focus on one operator $i \in \mathcal{J}$ and consider a user $u \in \mathcal{U}_i(t)$ served in slot t. The minimum transmit power per user according to SINR criteria is given by [36]:

$$P_u = P_0 - g_u - g_n + l_{n,u} + \psi_u + 10 \cdot \log_{10}(M_u)\,. \tag{6}$$

In the above equation P_0 is the receiver sensitivity for the specific service (here it is assumed $P_0 = -121\,dBm$), parameter $g_u = 2.14\,dBi$ represents the antenna gain of user u and $g_n = 2.14\,dBi$ represents the antenna gain of BS n, $l_{n,u}$ is the path loss between the BS n and user u, ψ_u is the shadow component derived by a log normal distribution with standard deviation equal to 8 dB and M_u is the number of resource blocks assigned to user u. The total RF out power of BS $n \in N_i$ at time t is given by

$$P_n(t) = \sum_{u=1}^{U_i^n(t)} P_u \tag{7}$$

Channel Model: To compute the channel characteristics between a BS and a user we use an empirical formulation for urban environments. Based on [20] we use the average value of the Line of Sight (LOS) and Non Line of Sight (NLOS) models between user and MBS. We implement this model for all users connected to MBS or mBS to simplify computations. The path loss is given by

$$\mathrm{l}_{n,u} = 16.8 + 33.2 \cdot \log_{10}(d_{n,u}) \tag{8}$$

where $d_{n,u}$ is the distance (meters) between user u and BS n.

Other issues: For the simulations, we assumed that all users require the same QoS and thus all active users in the network were assigned the same number of subcarriers. In order to define a relationship between the RF out power of the BS and the number of served users, we developed a stochastic model that randomly generates users around a BS. We generated 100 random scenarios with users spread uniformly on a disc of radius *3 km* around the BS. The independent scenarios were executed for 1 to 200 users.

The relationship between the number of users served and the RF out power (in Watts) is shown in Fig. 3. A curve fitting approximation was used to derive the linear relationship. The vertical axis represents the RF out power P_n^{RF} of the BS $n \in \mathcal{N}$, and the horizontal axis the number of users that are served served. As a next step, we incorporate this linear equation into the general BS power model that is given in [35], and correlates the power consumption of the BS with its RF out power, i.e.:

$$C_n^{RF} = \gamma_n P_n^{RF} + b_n, \tag{9}$$

where $\gamma_n = 22.6$ if $n \in \mathcal{M}_i$ and $P_{\max} = 5\,Watts$, and $\gamma_n = 5.5$ if $n \in \mathcal{K}_i$. Parameter b_n is the same as expressed in (5). Eq. (5) now describes the BS power needs as a function of the active users in the cell, rather than of the RF out power.

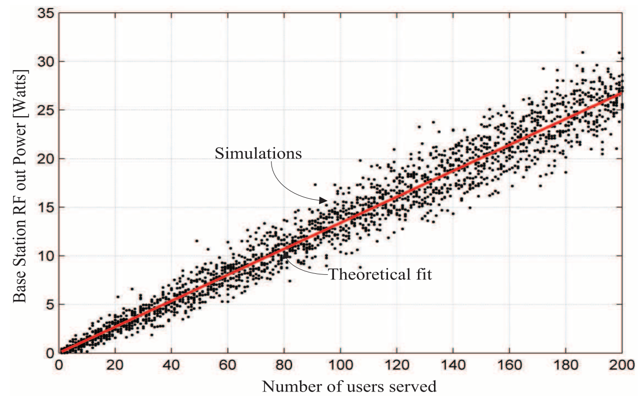

Fig. 3. Base station power consumption as a function of number of served users. The results were drawn from 100 experiments where up to 200 users were randomly placed in a radius of 3 km from the BS.

For the simulation results we assumed that users are uniformly distributed in the coverage area of the MNO and thus they are equally spread among the BSs of the network. Moreover, we assumed that mBSs have 4 times smaller coverage than MBSs.

B. Problem Statement

In general, as we noted, two types of sharing schemes are possible: *network sharing* and *base station sharing*. Network sharing refers to the case where all the BSs of a MNO in a certain area are switched off (concurrently), and the traffic is migrated toward other operators that serve the area. In this case roaming has temporal characteristics that make the sharing scheme more practical. On the other hand, BS sharing refers to the case where the BSs of one MNO are shared to provide energy savings. The transition state of the network infrastructure of one MNO is smooth, meaning that gradually the BSs' of MNO i are set in sleep mode by migrating traffic to the other MNOs $j \in \mathcal{J} \setminus \{i\}$. In this case, roaming has both temporal and spatial characteristics, which render this scheme more difficult to implement in practice. Our goal in this work is to study the inter-network sharing scenario. Note however, that the two schemes differ in the granularity of the decisions that need to be made, and thus network sharing for very small areas essentially converges to base station sharing.

We denote with $x_i(t) \in \{0, 1\}$ the decision of each operator $i \in \mathcal{J}$ to switch off ($x_i(t) = 0$), or not ($x_i(t) = 1$) its network in area $\mathbb{A}$, during time slot t. We also define for each operator i the overall on-off policy for the time period T:

$$\boldsymbol{x}_i = (x_i(t) : t = 1, \ldots, T)\,, \tag{10}$$

and introduce the matrix $\boldsymbol{x} = (\boldsymbol{x}_i : i \in \mathcal{J})$ which denotes the switching off policy of the MNOs.

Additionally, for each operator i we define the *roaming variables* $y_{ij}(t) \geq 0$ which determine the amount of operator i's traffic that will be routed to operator j, when $x_j(t) = 1$. Clearly, it should hold:

$$\sum_{j \in \mathcal{J}} y_{ij}(t) = f_i(t),\ \forall\, i \in \mathcal{J},\ t = 1, 2, \ldots, T\,, \tag{11}$$

TABLE I
KEY NOTATIONS

Symbol	Physical Meaning
$x_i(t)$	0-1 network activation decision of operator i, in t
$y_{ij}(t)$	Traffic of MNO i routed to operator j
p_i	Price paid by/to i for his roaming services
$f_i(t)$	Aggregate traffic of operator i in slot t, area $\mathbb{A}$
$\boldsymbol{f}_i$	Aggregate traffic of operator i in period T, area $\mathbb{A}$
$f_i^n(t)$	Aggregate traffic of BS $n \in \mathcal{N}_i$, slot t
$\boldsymbol{U}_i(t)$	Number of users of operator i, slot t
$U_i^n(t)$	Number of users of operator i under BS n in slot t
$C_n(U_i^n(t))$	Energy consumption of BS $n \in \mathcal{N}_i$ in slot t
$J_i^t(f_i(t))$	Servicing cost of i during slot t
$J_i(\boldsymbol{f}_i)$	Servicing cost of i during period T

where $y_{ii}(t) = 0$ denotes the traffic that is served by the same operator. We also define the roaming policy for each MNO $i \in \mathcal{J}$ as follows:

$$\boldsymbol{y}_i = \big(y_{ij}(t) : j \in \mathcal{J}, t = 1, \ldots, T\big) , \tag{12}$$

and $\boldsymbol{y} = \big(\boldsymbol{y}_i : i \in \mathcal{J}\big)$. Finally, we denote with $p_i \in \mathbb{R}$ the amount of money that operator i pays ($p_i \geq 0$) or is being paid ($p_i < 0$), for having its traffic served or for serving traffic of other operators, respectively. We define also the vector of payments $\boldsymbol{p} = (p_i : i \in \mathcal{J})$. At this point, we can formally define the problem under consideration as follows:

Cooperative Network Sharing Problem. *Given the aggregate traffic pattern of the operators $\boldsymbol{f}$, and the servicing cost functions $J_i(\cdot)$, $i \in \mathcal{J}$, find (i) the switching off policy $\boldsymbol{x}$, and the roaming policy $\boldsymbol{y}$ that minimize the aggregate servicing cost of all operators, and (ii) the payment policy $\boldsymbol{p}$ that yields a fair cost sharing among operators.*

III. COALITIONAL GAME FOR NETWORK SHARING

We employ coalitional game theory [26] in order to model and analyze the MNOs interactions. First, we devise the switching and traffic roaming (servicing) policy that minimizes the aggregate cost for all operators. Accordingly, we determine how the benefits of the cooperation, i.e., the reduction of the cost, should be shared among the different operators. This is crucial for ensuring that they will agree to collaborate.

A. Minimum Cost Cooperation

The main variables and functions of our problem are depicted in Table I. In mathematic terms, this problem can be written as follows:

$$\min_{\boldsymbol{x},\boldsymbol{y}} \sum_{i \in \mathcal{J}} J_i^{\mathcal{S}}(\boldsymbol{x}, \boldsymbol{y}) , \tag{13}$$

where $J_i^{S}(\cdot)$ is the servicing cost of operator $i \in \mathcal{J}$ when it participates in coalition $\mathcal{S}$, under the cooperation strategy $(\boldsymbol{x}, \boldsymbol{y})$ which determines when it will be active and how much traffic it will serve. As it will be clear in the sequel, $\boldsymbol{x}$ and $\boldsymbol{y}$ should satisfy certain constraints. Interestingly yet not-surprisingly, when we employ the cost functions described in the previous section, assuming that the energy prices q^t, $t = 1, \ldots, T$ are constant, the problem can be casted as a facility location problem. This is a well-known class of NP-hard problems, but many algorithms with tight approximation ratios are known, and there are even more heuristic solutions [22].

Let us first provide a description of the problem mapping for slot t. Each MNO $i \in \mathcal{J}$ represents a facility that can provide service if open ($x_i(t) = 1$) for the traffic emanating from the area of interest. The *opening cost* for each facility is the aggregate energy consumption cost of its BSs at zero load, i.e.,

$$B_i = \sum_{n=1}^{N_i} b_n . \tag{14}$$

At the same time, each operator $i \in \mathcal{J}$ incurs a certain marginal servicing cost per each (very small) additional unit of aggregate traffic Δf that it admits. Namely, based on the traffic allocation policy (i.e., the $L_i(\cdot)$ rule), this load is allocated to the $\mathcal{N}_i$ BSs resulting in a total additional (marginal) cost:

$$A_i = \sum_{n=1}^{N_i} a_n \Delta f_i^n(t) . \tag{15}$$

Additionally, each operator has a maximum servicing capacity which is characterized by the minimum capacity of its base station(s) in area $\mathbb{A}$. In other words, since (i) we take decisions for the entire set of the BSs of each MNO, and (ii) the traffic load $f_i(t)$ is uniformly distributed in $\mathbb{A}$, the MNO can provide service up to the point that the first BS will be congested[5]. We denote with W_i the quantity of the load $f_i(t)$ that can be admitted before that point, and which is considered constant across T. In general, this bound depends both on the type of the BSs that MNO $i \in \mathcal{J}$ uses, and on its deployment plan. Hence, for each activated MNO $i \in \mathcal{J}$ the following constraint should be respected:

$$\sum_{j \in \mathcal{J}} y_{ji}(t) \leq W_i . \tag{16}$$

The overall minimum-cost servicing problem for a set $\mathcal{S}$ of cooperating MNOs, under the above assumptions, can be thus written as follows:

$$\min_{\boldsymbol{x},\boldsymbol{y}} \sum_{i \in \mathcal{S}} \sum_{t=1}^{T} x_i(t) B_i + \sum_{j \in \mathcal{S}} \sum_{i \in \mathcal{S}} \sum_{t=1}^{T} y_{ji}(t) A_i \tag{17}$$

s.t.

$$\sum_{j \in \mathcal{S}} y_{ji}(t) \leq W_i x_i(t) , \ \forall\, i \in \mathcal{S},\ t = 1, \ldots, T . \tag{18}$$

$$\sum_{j \in \mathcal{S}} y_{ij}(t) \geq f_i(t),\ \forall\, i \in \mathcal{S},\ t = 1, \ldots, T . \tag{19}$$

$$x_i(t) \in \{0, 1\},\ y_{ij}(t) \in [0, f_i(t)],\ \forall\, i, j \in \mathcal{J}, t = 1, \ldots, T . \tag{20}$$

Constraints (18) ensure that each MNO will admit traffic only if it is activated, and that the served traffic cannot exceed its effective capacity. On the other hand, constraints (19) ensure that the

[5]Note that our formulation does not include user association or traffic routing within each MNO's network. However, even for such scenarios and since we adopt a macroscopic approach, the MNOs' servicing capacity will be eventually reached when the fist BS cannot serve traffic from a certain subarea, and this traffic cannot be allocated to another BS.

demand for each MNO will be fully served (and hence the entire demand in area $\mathbb{A}$). Finally, the set of eq. (20) denote the integrality constraint for the activation decision of the MNOs, and the traffic routing decisions across the different operators.

Since we don't consider routing decisions within each operator, and because we study the average user traffic in area $\mathbb{A}$, the above problem can be identified as a single-demand node capacitated facility location problem [24], [38]. Each MNO is a facility that has a hard capacity constraint, and a possibly different opening and servicing cost. Interestingly, this problem can be solved with a greedy algorithm that yields an optimal solution having the property that at most one facility is fractionally open [24]. For our problem, this means that, in order to achieve the maximum cost saving, there is a possibility that one operator (at most) will have to remain open for only a fraction of the time period T.

The main idea of the algorithm is to find the MNO with the lowest joint opening and servicing cost per unit of traffic, and assign to it as much traffic as possible[6]. When this MNO will be congested, the algorithm iteratively identifies the operator with the next smallest joint cost term, and assigns the remaining traffic until it reaches the capacity, or all the traffic is served. The detailed procedure is given in Algorithm 1 which follows the analysis in [24]. First, let us introduce the variable $Y_i(t) = \sum_{j\in\mathcal{J}} y_{ji}(t)$, which indicates how much traffic operator i admits if it is open. One can observe that for any feasible solution $(\boldsymbol{x}, \boldsymbol{y})$ we can set $\hat{x}_i(t) = Y_i(t)/W_i$, and obtain another feasible solution $(\hat{\boldsymbol{x}}, \boldsymbol{y})$. This means that we can omit the $x_i(t)$ variables and rewrite the objective of the above optimization problem as follows:

$$\min_{\{Y_i(t),\, i\in\mathcal{J},\, t=1,\ldots,T\}} \sum_{i\in\mathcal{S}}\sum_{t=1}^{T}\left(\frac{B_i}{W_i}+A_i\right)Y_i(t) \tag{21}$$

After this transformation, it is easy to follow Algorithm 1. First, we initialize the policy having all MNOs switched off at the beginning (line 2). For each slot within the time period of interest (line 4), and as long as there is unassigned traffic (line 7), we iteratively select the MNO with the lowest ratio (line 8), activate it, and assign the traffic it can serve, unless there is less unserved traffic than MNO k's capacity (line 9). Accordingly, we update the sets of already activated and remaining MNOs (line 10) and repeat the above steps. When all the demand in slot t has been assigned to the activated operators, we need to derive the detailed routing policy $y^*_{ij}(t)$ based on the optimal values $Y^*_i(t)$ (line 11). Note that there are many possible ways to satisfy constraints (22), all of which yield the same minimum servicing cost. We can simply apply a round robin filling-capacity algorithm. Finally, the above analysis can be employed to find the optimal servicing policy for any set $\mathcal{S}$ of MNOs, and of course for the entire set $\mathcal{J}$.

Algorithm 1 might yield a solution that requires a facility to be open only for a certain time period within T (fractional solution). Alternatively, one can obtain a solution where all facility opening decisions are strictly integral, but the outcome is suboptimal. On the other hand, there exist known tight approximation algorithms for this class of problems that can be employed if needed, e.g., see [39]. For the problem under consideration, since the number of MNOs servicing a certain area is expected to be relatively small [10] we can afford both of these approaches.

Algorithm 1. Greedy Algorithm for Solving the Min-Cost MNO Cooperation Problem

1 **Input**: $B_i, A_i, W_i, \boldsymbol{f}_i,\ i \in \mathcal{J}$;
2 **Initialization**: $x_i(t) = 0,\ y_{ij}(t) = 0,\ \forall i, j \in \mathcal{J},\ t = 1, 2, \ldots, T$;
3 $t \leftarrow 0$; % Initialize the time
4 **while** $t < T$ **do**
5 $\quad t \leftarrow t + 1$;
6 $\quad \mathcal{B} \leftarrow \mathcal{J};\ \mathcal{D} \leftarrow \emptyset$;
7 $\quad$ **while** $\sum_{k\in\mathcal{D}} Y_k(t) < \sum_{i\in\mathcal{B}} f_i(t)$ **do**
8 $\quad\quad k = argmin_{i\in\mathcal{B}}\{A_i + (B_i/W_i)\}$;
9 $\quad\quad x^*_k(t) \leftarrow 1;\ Y^*_k(t) = \min\{W_k, \sum_{i\in\mathcal{B}} f_i(t)\}$;
10 $\quad\quad \mathcal{D} \leftarrow \mathcal{D}\cup\{k\};\ \mathcal{B} \leftarrow \mathcal{B}\setminus\{k\}$;
$\quad$ **end**
11 $\quad$ Find any roaming policy $\boldsymbol{y}^*$ that satisfies the following set of conditions $\forall i \in \mathcal{J}$:

$$\sum_{j\in\mathcal{J}} y^*_{jk}(t) = Y^*_k(t),\ \forall k \in \mathcal{D},\ \text{and} \sum_{k\in\mathcal{D}} y^*_{jk}(t) = f_i(t) \tag{22}$$

end
12 **Output**: $\boldsymbol{x}^*,\ \boldsymbol{y}^*$;

B. The Coalitional Game and the Shapley Value Criterion

Clearly, in order to agree to cooperate, each MNO should (i) reduce its cost by participating in the inter-network sharing scheme, and (ii) receive a fair portion of the total cost-reduction that is jointly achieved by the operators. In order to study if these conditions can be satisfied for all MNOs, we define the operators' transferable utility (TU) coalitional game $G_M = \{\mathcal{J}, u\}$ where $\mathcal{J}$ is the set of all MNOs, and $u : \mathcal{S} \rightarrow \mathbb{R}^+$ is the so-called *characteristic function* that assigns a positive scalar value to each coalition. That is, each subset of operators $\mathcal{S} \subseteq \mathcal{J}$ that decide to cooperate, succeeds in reducing their total energy cost:

$$u(\mathcal{S}) = \sum_{i\in\mathcal{S}} J_i(\boldsymbol{f}_i) - \sum_{i\in\mathcal{S}} J^{\mathcal{S}}_i(\mathbf{x}^*, \mathbf{y}^*) \tag{23}$$

This benefit can be dispersed among the MNOs in any arbitrary fashion through the side-payments, i.e., the charged roaming fees. Also, it is important to emphasize that $J^{\mathcal{S}}_i(\mathbf{x}^*, \mathbf{y}^*)$ can be larger than the servicing cost when the MNO acts in an independent fashion, in case it has to serve traffic from other operators.

The critical question in TU coalitional games is how the value of each coalition will be shared among its members. In turn, this determines the coalitions that will be formed. A particularly important question is whether the *grand coalition* will

[6]Here, we have also assumed, without loss of generality, that the charged prices q^t are equal for all the MNOs. Notice however that our analysis is directly applicable for scenarios where each MNO pays a possible different price to the energy provider.

be stable. Technically, this means that no operator will have an incentive to deviate and either act independently or cooperate with only a subset of other operators.

We use the concept of Shapley value [30], which is an axiomatic fairness criterion, to find each operator's share of the cost reduction. In detail, for each player i participating in a coalition $\mathcal{S} \subseteq \mathcal{J}$, the Shapley value $\phi_i(\mathcal{S}, u)$ should satisfy the following axioms [26], [37]:

- **Efficiency**: $\sum_{i \in \mathcal{S}} \phi_i(\mathcal{S}, u) = u(\mathcal{S})$
- **Symmetry**: If for all $\mathcal{S}' \subseteq \mathcal{S} \setminus \{i, j\}$ it holds $u(\mathcal{S}' \cup \{i\}) = u(\mathcal{S}' \cup \{j\})$, then $\phi_i(\mathcal{S}, u) = \phi_j(\mathcal{S}, u)$.
- **Balanced Contribution**: $\phi_i(\mathcal{S}, u) - \phi_i(\mathcal{S}\{j\}, u) = \phi_j(\mathcal{S}, u) - \phi_j(\mathcal{S}\{i\}, u)$.

There exists a closed form expression for finding the Shapley value of each player:

$$\phi_i(\mathcal{S}, u) = \sum_{S \subset \mathcal{J}} \frac{|S|!(|\mathcal{J}| - |S| - 1)!}{|\mathcal{J}|!} \left(u(\mathcal{S} \cup \{i\}) - u(\mathcal{S})\right) \quad (24)$$

The important point is the following. When the coalitional game is superadditive and supermodular, then allocating the Shapley values to each player ensures that the grand coalition is stable [29]. In other words, the *core* of the game is non-empty and no operator has an incentive to deviate unilaterally and no subgroup of operators can achieve a better outcome by forming a disjoint coalition (other than the grand coalition).

Once the Shapley values are determined, i.e., the cost shares for each operator, we can derive the optimal price vector $\boldsymbol{p}^*$ that achieves this fair cost sharing. Specifically, the latter should be selected as follows:

$$p_i = \phi_i(\mathcal{S}, u) - (J_i(\boldsymbol{f}_i) - J_i^{\mathcal{S}}(\boldsymbol{x}^*, \boldsymbol{y}^*)) \quad (25)$$

Notice that p_i can be positive or negative, based on whether MNO $i \in \mathcal{J}$ has to pay or needs to be reimbursed for its participation in the coalition $\mathcal{S}$. Therefore the final utility that MNO i perceives is the sum of $J_i^S(\boldsymbol{x}^*, \boldsymbol{y}^*)$, i.e., the incurred cost, and the price p_i.

C. Properties of Game G_M

We now prove that game G_M is superadditive and supermodular.

Lemma 1: The characteristic function u of the game G_M is *superadditive* [26] if the following condition holds:

$$u(\mathcal{S}_1 \cup \mathcal{S}_2) \geq u(\mathcal{S}_1) + u(\mathcal{S}_2), \ \forall \mathcal{S}_1, \mathcal{S}_2 \subset \mathcal{N}, \ \mathcal{S}_1 \cap \mathcal{S}_2 = \emptyset$$

Proof: The superadditivity property can be easily verified if we consider that cooperation does not entail any additional cost to operators, e.g., they do not have to buy additional equipment or pay fees to third parties (e.g., to the state, etc). Therefore, when two operators cooperate (or, two disjoint sets of operators), in the worst case they can achieve the same performance of their previous (standalone/disjoint) operation. That is, they can revert back to their non-cooperative behavior to obtain their non-cooperative payoffs. ■

This ensures that the Shapley value is individual rational and hence no player (operator) has an incentive to deviate (since his benefit increases when he participates in any coalition). ■

TABLE II
SIMULATION PARAMETERS FOR THE WEEKLY PROFILE

MNO i	i=1	i=2	i=3
Maximum served users in $\mathbb{A}$	200	200	200
Number of MBSs	5	5	5
Number of mBSs	10	10	10
a_n in Watts/user for MBSs	3	3	3
b_n in Watts for MBSs	200	400	800
a_n in Watts/user for mBSs	0.7	0.7	0.7
b_n in Watts for mBSs	15	30	60

Lemma 2: The characteristic function $u(\cdot)$ of the game G_M is *supermodular* [26]:

$$u(\mathcal{S} \cup \{i\}) - u(\mathcal{S}) \leq u(\mathcal{Q} \cup \{i\}) - u(\mathcal{Q}), \ \forall \mathcal{S} \subseteq \mathcal{Q} \subseteq \mathcal{N} \setminus \{i\}$$

Proof: We have the following:

$$u(S) = \sum_{j \in \mathcal{S}} J_j(\boldsymbol{f}_j) - \sum_{j \in \mathcal{S}} J_j^{\mathcal{S}}(x_j^o, y_{-j}^o) \quad (26)$$

with $(x_j^o, y_{-j}^o, \forall j \in \mathcal{S})$, being the optimal policy, i.e., the solution of (17)–(20),

$$u(\mathcal{S} \cup \{i\}) = \sum_{j \in \mathcal{S} \cup \{i\}} J_j(\boldsymbol{f}_j) - \sum_{j \in \mathcal{S} \cup \{i\}} J_j^{\mathcal{S} \cup \{i\}}(x_j^*, y_{-j}^*) \quad (27)$$

with the optimal policy $(x_j^*, y_{-j}^*, \forall j \in S \cup \{i\})$,

$$u(\mathcal{Q}) = \sum_{j \in \mathcal{Q}} J_j(\boldsymbol{f}_j) - \sum_{j \in \mathcal{Q}} J_j^{\mathcal{Q}}(x_j', y_{-j}') \quad (28)$$

with the optimal policy $(x_j', y_{-j}', \forall j \in \mathcal{Q})$, and

$$u(\mathcal{Q} \cup \{i\}) = \sum_{j \in \mathcal{Q} \cup \{i\}} J_j(\boldsymbol{f}_j) - \sum_{j \in \mathcal{Q} \cup \{i\}} J_j^{\mathcal{Q} \cup \{i\}}(x_j^\dagger, y_{-j}^\dagger) \quad (29)$$

with $(x_j^\dagger, \boldsymbol{y}_{-j}^\dagger, \forall j \in S \cup \{i\})$.

Using the definition of supermodularity and substituting from the above equations, we get:

$$\sum_{j \in \mathcal{S} \cup \{i\}} J_j^{\mathcal{S} \cup \{i\}}(x_j^*, \boldsymbol{y}_{-j}^*) - \sum_{j \in \mathcal{S}} J_j^{\mathcal{S}}(x_j^o, \boldsymbol{y}_{-j}^o) \geq \sum_{j \in \mathcal{Q} \cup \{i\}} J_j^{\mathcal{Q} \cup \{i\}}(x_j^\dagger, \boldsymbol{y}_{-j}^\dagger) - \sum_{j \in \mathcal{Q}} J_j^{\mathcal{Q}}(x_j', \boldsymbol{y}_{-j}') \quad (30)$$

It is easy to see that inequality (30) holds. The critical observation is the following. When optimizing the strategy for a larger coalition, e.g., $\mathcal{Q}$, then the value of the minimum cost is upper bounded by the respective (minimum) cost for a smaller coalition $\mathcal{S}$ plus the non-cooperation costs for the operators that belong to the set $\mathcal{Q} \setminus \mathcal{S}$. This can be ensured if the coalition $\mathcal{Q}$ follows the same strategy, i.e., matrices $\boldsymbol{x}, \boldsymbol{y}$, with $\mathcal{S}$ for all the operators that belong to both sets, $\forall j \in \mathcal{Q} \cap \mathcal{S}$, and then have the remaining operators $\forall j \in \mathcal{Q} \setminus \mathcal{S}$ operate as if in the independent (non-cooperative) mode.

Following this rationale, we can write:

$$\sum_{j \in \mathcal{Q}} J_j^{\mathcal{Q}}(x_j', \boldsymbol{y}_{-j}') \leq \sum_{j \in \mathcal{S}} J_j^{\mathcal{S}}(x_j^o, \boldsymbol{y}_{-j}^o) + \sum_{j \in \mathcal{Q} \setminus \mathcal{S}} J_j(\boldsymbol{f}_j) \quad (31)$$

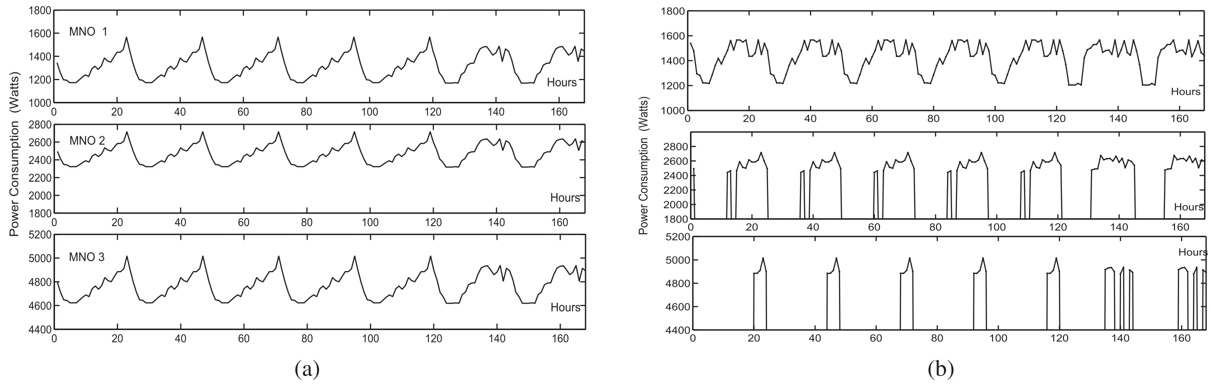

Fig. 4. Power consumption of three MNOs for a weekly traffic profile. From top to bottom: MNO 1, MNO 2, MNO 3. Figure (a): Non-cooperation scenario where each MNO serves its own traffic and incurs a different power consumption. Figure (b): Cooperation scenario where traffic from MNO 2 and MNO 3 is routed to MNO 1 in certain time slots. Note that the lowest-values (flat intervals) for MNO 2 and 3 represent zero consumption.

by setting $x'_j \triangleq x^o_j,\ \forall j \in \mathcal{S} \cap \mathcal{Q}$, and $x'_j = 1,\ y_{ji} = 0,\ \forall i \in \mathcal{Q},\ j \in \mathcal{Q} \setminus \mathcal{S}$. Also, we have:

$$\sum_{j \in \mathcal{Q}\cup\{i\}} J_j^{\mathcal{Q}\cup\{i\}}(\boldsymbol{f}_j, x_j^\dagger, \boldsymbol{y}_{-j}^\dagger) \le \sum_{j \in \mathcal{S}\cup\{i\}} J_j^{\mathcal{S}\cup\{i\}}(\boldsymbol{f}_j, x_j^*, \boldsymbol{y}_{-j}^*) + \sum_{j \in \mathcal{Q}\cup\{i\}\setminus\mathcal{S}\cup\{i\}} J_j(\boldsymbol{f}_j) \quad (32)$$

by setting the routing and on-off variables accordingly. Obviously it holds:

$$\sum_{j \in \mathcal{Q}\cup\{i\}\setminus\mathcal{S}\cup\{i\}} J_j(\boldsymbol{f}_j) = \sum_{j \in \mathcal{Q}\setminus\mathcal{S}} J_j(\boldsymbol{f}_j) \quad (33)$$

Hence (30) follows directly, and this concludes the proof. ■

This means that no given subset of operators have an incentive to deviate from the grand coalition. Practically, the supermodularity property implies that as more operators join the coalition and cooperate, the cost is further reduced.

IV. Simulation Results

In this section we present a numerical analysis for a scenario with three MNOs. The MNOs are willing to cooperate towards the objective of increasing their overall energy savings. The MNOs might have the same or different network architectures. This means that the number, the type (MBS or mBS), and the location of the BSs can be generic. For the simulation results it was assumed that the MBS can absorb three times more traffic compared to the mBS, and the number of users are equally distributed among the MNOs. The simulation parameters were selected following measurement-based studies and industry reports [4], [6], [8], [18], [19], [25], [32].

A. Energy Savings

First, we quantify the energy savings that can be obtained by the cooperation of the MNOs, where some of them are put in sleep mode (in area $\mathbb{A}$), and their traffic is routed to the others. The simulation results concern the weekly traffic profile given in [10]. It is assumed that the three MNOs have similar network architectures, but differ in terms of the used BS technology. Therefore, they have different energy consumptions. For the results presented below, and unless otherwise specified, we assume that the energy price q^t is constant and equal to \$0.1 per kWh. The parameters are shown in Table II.

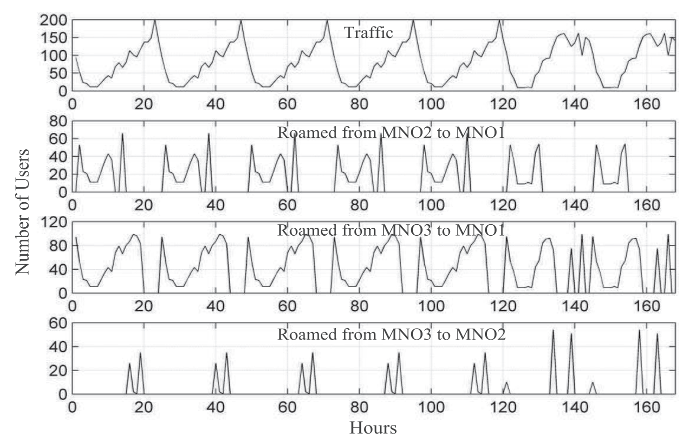

Fig. 5. Average traffic and roamed users among the three MNOs for the weekly traffic profile taken from [10].

TABLE III
ENERGY SAVINGS FOR THREE MNOS (KWH)

Coalition	MNO	Cost - No Cooperation	Cost - Co-operation	Savings (%)
{1, 2, 3}	$i = 1$	221	239	−8
	$i = 2$	415	243	41
	$i = 3$	801	202	74
	Total	1437	685	52
{1, 2}	$i = 1$	221	239	−8
	$i = 2$	415	161	61
	Total	636	392	38
{1, 3}	$i = 1$	221	239	−8
	$i = 3$	801	303	62
	Total	1022	535	47
{2, 3}	$i = 2$	415	425	−2
	$i = 3$	801	303	62
	Total	1216	728	40

The simulation results are plotted in Figs. 4 and 5. The figures present the power consumption (per hour) over one week for each MNO and the roamed users between the MNOs during the cooperation. In Fig. 4, each subplot gives the power

TABLE IV
SIMULATION PARAMETERS—EFFECT OF BS TECHNOLOGY

	MNO 1	MNO 2	MNO 3
Test 1	$a_n, \forall n \in \mathcal{N}_1$ constant, $b_n = 200W \rightarrow 600W$, step of $50W$, $\forall n \in \mathcal{M}_1$; $b_n = 15W \rightarrow 55W$ step of $5W$, $\forall n \in \mathcal{K}_1$.	Same as MNO 1	Same as MNO 1
Test 2	$b_n, \forall n \in \mathcal{N}_1$ constant , $a_n = 1W$/user $\rightarrow 5W$/user, step of $0.5W$ $\forall n \in \mathcal{M}_1$; $a_n = 0.2W$/user $\rightarrow 1.8W$/user, step of $0.2W$, $\forall n \in \mathcal{K}_1$	Same as MNO 1	Same as MNO 1
Test 3	$a_n = 3W$/user, $b_n = 400W$ $\forall n \in \mathcal{M}_1$, and $a_n = 0.7W$/user, $b_n = 30W$ $\forall n \in \mathcal{K}_1$	$a_n, \forall n \in \mathcal{N}_2$ is constant, $b_n = 200W \rightarrow 600W$, step of $50W$, $\forall n \in \mathcal{M}_2$; and $b_n = 15W \rightarrow 55W$, step of $5W$, $\forall n \in \mathcal{K}_2$.	$a_n, \forall n \in \mathcal{N}_3$ constant, $b_n = 600W \rightarrow 200W$, step of $50W$, $\forall n \in \mathcal{M}_3$; and $b_n = 55W \rightarrow 15W$ step of $5W$, $\forall n \in \mathcal{K}_3$.

consumption with (right) and without (left) implementing the cooperation strategy, for each MNO. It is shown that during very low traffic periods, two MNOs (MNOs 2 and 3) are switched off, and their traffic is migrated to MNO 1. In addition, it can be observed that in some occasions, the power consumption of MNO 1 is higher during the cooperation since it absorbs traffic from the remaining MNOs and increases its power consumption to satisfy the traffic (compare the left and right respective subfigures). From Table II we can observe that the the three MNOs use different BS technologies. MNO 1 has BSs with no-load losses parameters $b_n = 200$, MNO 2 BSs with $b_n = 400$, and MNO 3 BSs with $b_n = 800$, respectively. Thus, MNO 3 consumes more energy than the other operators when they don't cooperate. The simulation results present a migration of users to MNO 1, which is the most energy efficient; this strategy reduces the overall network consumption.

In Fig. 5 we see that when a MNO is set in sleep mode its users are roamed to the remaining active MNOs. Note that, in this scenario, most users are roamed from MNO 3 to MNO 1 as the former is set - most of the time - in sleep mode. Moreover, we observe that the amount of roamed traffic varies with time and reaches the lowest point during peak traffic hours. This results verifies the intuition that such cooperative schemes are beneficial when traffic load is low (or, medium) and hence the active base stations can additionally serve the traffic from the base stations that are switched off. Obviously, the total benefits of cooperation (for the coalition) depend on the traffic pattern in area$\mathbb{A}$. Table III presents the aggregated energy savings over one-week time period, for the scenarios where all three MNOs cooperate or only certain pairs of them. The minus sign in the percentage column represents increase of energy consumption when cooperation is implemented. We observe that when all MNOs cooperate we obtain the largest energy savings since in many slots two out of three MNOs are set in sleep mode. In general, overall energy savings of the order of 40%–50% are observed by implementing cooperation of MNOs. Individual MNO energy savings can reach 74% for the considered representative scenario.

B. *Effect of Base Station Technology*

This subsection presents the effect of the used BS technology upon the cooperation of the MNOs. Intuitively, the cooperation induces larger benefits when the MNOs are diverse in term of their network deployments and types of their base stations. In order to validate this intuition numerically we perform nine simulation steps (*simulation ids*), each one presenting a different configuration of parameters a_n and b_n of eq. (5). We investigate the effect of the *Shapley* value by distinguishing the three test scenarios summarized in Table IV.

In Test 1, we investigated the impact of parameter b_n. Namely, for this case, parameters a_n remain constant for each simulation and are equal to $a_n = 3$ Watts/user for the MBSs, and $a_n = 0.7$ Watts/user for the mBSs. Parameters b_n of the BSs are increasing in the same order, following the range given in Table IV. Thus, for each simulation, parameter b_n is increasing in 50 Watt steps for MBSs and in 5 Watt steps for mBSs, respectively. The scope of Test 1 is to highlight the significance of the no load losses of the BSs upon the cooperation strategy.

Test 2 studied the impact of parameter a_n. For this case, parameters b_n remain constant for each simulation and are set to $b_n = 400$ Watts for the MBSs and $b_n = 30$ Watts for the mBSs. Parameters a_n of the BSs are increasing in the same order, following the ranges given in Table IV. Thus, for each simulation, parameter a_n is increasing in *0.5 Watts/user* steps for MBSs, and in *0.2 Watts/user* steps for mBSs, respectively. The scope of Test 2 is to highlight the significance of the proportionality factor of the BSs upon the cooperation strategy.

The next simulation Test 3, investigates the effect when two MNOs present opposite characteristics in terms of the BS technology. Test 3 represents the case where during the simulations one MNO remains unchanged whereas the other two MNOs present opposite characteristics. More precisely, MNO 1 has $a_n = 3$ Watts/user and $b_n = 400$ Watts for the MBSs, and $a_n = 0.7$ Watts/user and $b_n = 30$ Watts for the mBSs, which are constant for all simulation steps. MNO 2 has the same settings as in Test 1, whereas MNO 3 has the same settings as in Test 1, but the parameter b_n decreases from the maximum towards the minimum value of the range presented in Table IV.

The results of experiments Test 1, Test 2 and Test 3 and the various combinations of the BSs' parameters, are presented in Fig. 6. It can be observed that the effect of parameter b_n is significant, whereas the effect of parameter a_n is negligible. This was expected, since the cooperation mainly depends on the energy savings that are directly related to the energy waste and thus the no-load power consumption of the BSs.

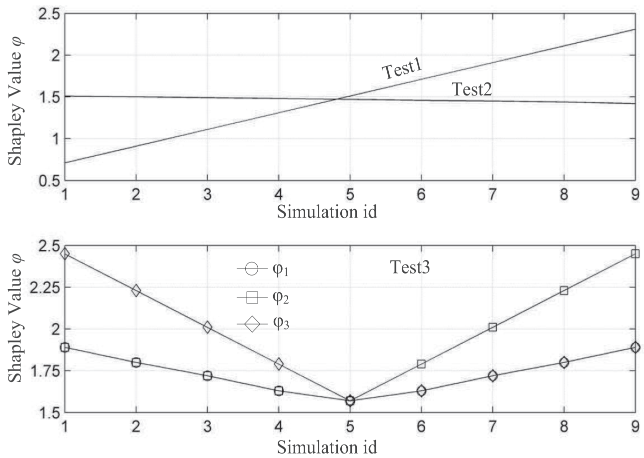

Fig. 6. Shapley values for the three MNOs in the cooperation scenarios Test 1, Test 2 and Test 3. Simulation id refers to the specific configuration as it is described in Table IV. For example, simulation id = 1 for Test 1 refers to the case that $b_n = 200$ for MBS, and $b_n = 15$ for mBS, while id = 2 refers to the case that these values are $b_n = 200 + 1 \cdot 50$, $b_n = 15 + 1 \cdot 5$, id = 3 to values $b_n = 200 + 2 \cdot 50$, $b_n = 15 + 2 \cdot 5$ and so on.

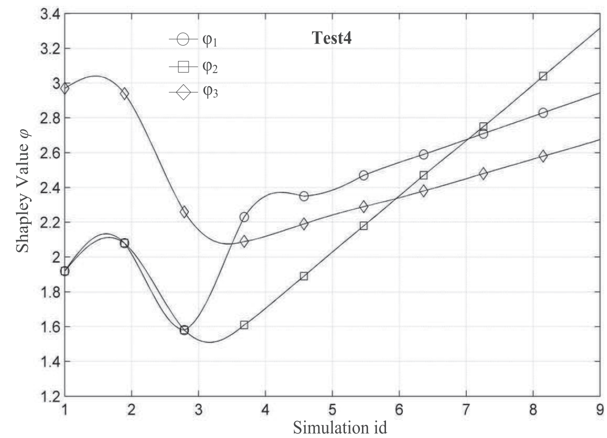

Fig. 7. Simulation results for Test 4. A generic network configuration has been considered where the three MNOs have diverse BS deployments as it is shown in Table V, while additionally the MNO 2 deployment changes (for Simulation Id). Specifically, simulation id = 1 corresponds to the case that $b_n = 200$ for MBS and $b_n = 15$ for mBS, simulation id = 2 to the case that $b_n = 200 + 1 \cdot 50$ for MBS, and $b_n = 15 + 1 \cdot 5$, id = 3 for $b_n = 200 + 2 \cdot 50$ for MBS, and $b_n = 15 + 2 \cdot 5$, and so on.

TABLE V
SIMULATION PARAMETERS FOR TEST 4

MNO i	i=1	i=2	i=3
Capacity	600	700	500
Number of MBSs	6	7	5
Number of mBSs	12	14	10
a_n in Watts/user for MBSs	3	3	3
b_n in Watts for MBSs	200	200-600	600
a_n in Watts/user for mBSs	0.7	0.7	0.7
b_n in Watts for mBSs	15	15-55	55

The same observation is valid also for the non-cooperative approach [12]. In general, it is found that when the BSs of the networks incorporate hardware equipment with large no-load power consumption, then cooperation between MNOs is vital. The cooperation yields lower savings when the BSs do not present high no-load power consumption.

Regarding Test 3, it is observed that there is symmetry around the simulation step 5, as expected. At simulation step 5, all MNOs have the same base station characteristics. It is observed that the higher gains are placed at the MNO with the most inefficient technology, since it causes the highest energy consumption. Thus, when the specific MNO switches off, the profits for the three players increases. In parallel, the remaining MNOs still present an increase in the their gains (Shapley value) by increasing the BS losses of the other MNO.

Test 4 represents the case for a generic network configuration. For this case we simulate three MNOs that present different characteristics in terms of capacity, BS technologies and number of MBSs and mBSs. The simulation parameters are presented in Table V and the simulation results in Fig. 7. It is shown that the Shapley value depends on the traffic, the network configuration and the number of BSs. These are directly related to the power consumption characteristics of the MNOs. After simulation step 4, the no-load power consumption of MNO 2 is becoming large, and this drives the overall increase of the *Shapley* value for all MNOs. This was to be expected, since the gains from the cooperation strategy are also increasing.

V. CONCLUSIONS

The increasing volume of mobile data traffic calls for innovative solutions such as the inter-network sharing among different mobile network operators. Although such approaches have a huge potential in terms of cost savings, and despite the fact that related efforts already appeared in the market [9], they haven't received adequate focus from the research community. In this work we proved that, under some mild conditions, RAN sharing is an incentive compatible policy that allows all the co-existing operators to work together and reduce their servicing costs. Moreover, we provided a detailed optimization framework for devising the minimum servicing cost policy for different network deployment and traffic scenarios. This policy dictates which operators should switch off their networks and how their traffic will be served by the remaining ones. We employed a coalitional game theoretic formulation and designed the roaming fees such that the cost benefits are dispersed among the participants in a fair fashion according to the Shapley value rule. The numerical analysis revealed that the profits generated by the cooperation strategy are very sensitive to the network technology as they heavily depend on the no-load power consumption of the base stations. Overall, the energy savings were found to be in the order of 40–50%.

In terms of actual implementation, cooperation can be supported by a "horizontal" service provider that will coordinate the access network infrastructure of the different MNOs and will apply the proposed roaming and charging rules. Moreover, our analysis can be applied in settings where the operators offer different QoS to their users. This diversity can be captured through the energy cost functions of the base stations, which yield higher operating expenses per user as the offered QoS increases. Therefore, our analysis is generic and can address a variety of different scenarios. Among them, of particular interest are settings where the MNOs rely on renewable energy resources with time-varying and random production [40], [41], and hence the inter-network sharing is even more crucial.

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