Multiobjective Auction-Based Switching-Off Scheme in Heterogeneous Networks: To Bid or Not to Bid?

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***Abstract*—The emerging data traffic demand has caused a massive deployment of network infrastructure, including macro base stations (BSs) and small cells (SCs), leading to increased energy consumption and expenditures. However, the network underutilization during low traffic periods (e.g., night zone) enables the mobile network operators (MNOs) to save energy by having their traffic served by third-party SCs, thus being able to switch off their BSs. In this paper, we propose a novel market approach to foster the opportunistic utilization of the unexploited SCs capacity, where the MNOs, instead of requesting the maximum capacity to meet their highest traffic expectations, offer a set of bids requesting different amounts of resources from the third-party SCs at lower costs. Motivated by the conflicting financial interests of the MNOs and the third party, the restricted capacity of the SCs that is not adequate to carry the whole traffic in multioperator scenarios, and the necessity for energy-efficient solutions, we introduce a combinatorial auction framework, which includes 1) a bidding strategy, 2) a resource-allocation scheme, and 3) a pricing rule. We propose a multiobjective framework as an energy- and cost-efficient solution for the resource-allocation problem, and we provide extensive analytical and experimental results to estimate the potential energy and cost savings that can be achieved. In addition, we investigate the conditions under which the MNOs and the third-party companies should take part in the proposed auction.**

***Index Terms*—Auction, energy efficiency, game theory, green networking, heterogeneous networks (HetNets), multiobjective optimization, offloading, switching off.**

I. Introduction

A. Motivation

The rapid expansion of mobile services, along with the emerging demand for multimedia applications, driven by the widespread use of laptops, tablets, and smart devices, has led to an impressive growth of data traffic during the last few years. Global mobile data traffic is expected to increase nearly tenfold, reaching 24.3 EB per month by 2019 [1]. Hence, mobile network operators (MNOs[1]) seek to extend their infrastructure by installing more base stations (BSs). In an effort to increase the capacity of their network and meet these pressing traffic demands, they also lease capacity and bandwidth resources from third parties, who deploy low-powered small-cell (SC) networks to provide enhanced services via traffic offloading from macro BSs to SCs during peak hours [2]. For instance, Nokia Networks [3] has recently built networks of interconnected SCs, enabling operators to extend the coverage and increase the capacity of existing macro networks. The involvement of various entities of corporate nature with different financial goals generates a new ecosystem with interesting dynamics to be studied. To that end, in [4], the economics of offloading are investigated, whereas auction theory is used to model economic transactions between conflicting parties in several works [5]–[7] through offloading schemes with auction-based resource-allocation problems.

The dense heterogeneous networks (HetNets) imply significant increase in the capital and operational expenditures (CapEx and OpEx) of MNOs [8], and as a result, there is a strong motivation to investigate energy-efficient solutions to bring down the energy consumption and the cost of networks. This goal can be accomplished through the switching off of the underutilized nodes when the traffic is significantly low. Since the BSs are the most power hungry and expensive components of the networks [9], the research community has shifted toward the investigation of BS switching-off schemes [10]–[15]. Despite their promising results, these works examine only one tier of macro BSs, whereas the presence of multiple MNOs raises new challenges and open issues.

The SC deployment in current HetNets can be the key to implementing novel energy and cost-efficient solutions. By encouraging the traffic offloading from BSs to SCs during low traffic periods, when the SC resources are most likely to remain unused, part of the BS infrastructure can be switched off. Given that the energy consumption of the BSs is considerably higher with respect to the SCs, even when the traffic load is low, such solutions can yield high energy gains for the MNOs. Thus, offloading can be exploited to concentrate the users to the SCs

[1]The terms “MNO” and “operator” will be used interchangeably in the remainder of this paper.

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and allow the BSs with no traffic to be switched off. However, despite the potential gains of the opportunistic exploitation of the capacity of SCs and the deactivation of the redundant BSs during low traffic conditions, very few research works exist in the literature so far.

An overview of the existing techniques in energy-efficient network planning is presented in [16], highlighting the advantages and the shortcomings of the algorithms and revealing the open issues that should be further studied in the field of HetNets and operators' collaboration. In the same context, in [17], an auction-based offloading scheme is proposed for the BS switching off, where the operators submit a bidding value, and a third party's income optimization approach is followed to solve the resource-allocation problem. However, only a particular network configuration is considered, where it is assumed that the SC capacity is sufficient to serve the traffic of the network, allowing the switching off of all the BSs.

Despite the clear benefits of the BSs switching off via offloading, the presence of multiple MNOs in the same area [18] would complicate the application of this scheme since the SCs may not be able to fully support the network traffic. Another limitation of the auction-based state-of-the-art works [5], [6], [17] consists in the fact that the MNOs propose a single bidding value for the requested capacity, based on the maximum predictions about the traffic that they are willing to offload. However, these predictions do not always correspond to the real traffic values, which can be significantly lower than the maximum values, leading to increased costs for the operators and inefficient use of the SC capacity resources.

B. Contribution

In this paper, motivated by the aforementioned issues, we propose a novel energy-efficient solution for dense HetNets, which considers the interests of the involved parties (MNOs and third party) and the time-varying traffic characteristics. More specifically, we introduce an offloading mechanism, where the operators lease the capacity of an SC network owned by a third party, to be able to switch off their BSs and maximize their energy efficiency, when the traffic demand is low. The MNOs request capacity from several SCs and can only switch off their BSs if all their requests are satisfied, enabling them to offload all their traffic to the SC network.

To that end, the allocation of the SC resources among a set of competing MNOs is mathematically formulated as an auction. Since the exact resource requirements of the network are unknown beforehand, the MNOs employ past reports to predict the maximum expected traffic load. Then, exploiting the fact that, with a high probability, the actual traffic will be lower than the predicted maximum (especially during low traffic periods), the MNOs submit a set of bids to the SCs, requesting for lower capacity resources (with respect to the maximum estimated requirements). With this approach, the SC resources can be more efficiently utilized, and the MNOs are likely to pay a lower price for the leased capacity, taking a small risk of not being able to serve all users under some circumstances (i.e., when the traffic approaches the maximum predictions and the leased capacity is not sufficient). Our key contribution is to study this very interesting trade-off between the potential energy and financial gains of this solution and the risk of not fully satisfying all the users, thus providing the MNOs with the necessary insights to decide whether it is profitable to participate in the auction, depending on their tolerance to the potential loss of some users.

In addition, the conflicting interests of the involved parties are also taken into consideration. On the one hand, the MNOs aim to reduce their energy consumption and expenditures by offloading their traffic and switching off their BS infrastructure. However, to deactivate a BS, all its traffic should be offloaded to the SC network (i.e., the MNO should win in all the auctions involving the particular BS). On the other hand, the third party wants to maximize its income by leasing the maximum possible amount for resources to the MNOs. However, the resource allocation policy that maximizes the third party's income may not enable the operators to switch off their BSs. Our proposed auction-based strategy takes into account these conflicting interests to achieve a feasible, efficient, and energy-saving resource-allocation scheme.

In summary, the contribution of this paper is described as follows.

1) *Bidding Strategy*: We propose a novel bidding strategy, where MNOs submit a set of bids (and not only one bid) to the third party, requesting different capacity resources, based on the predictions about their maximum traffic. The diversity of bids allows more offloading opportunities, which is profitable for both the MNOs and the third party.
2) *Auction Design and Switching Off Decision*: We design an auction scheme that enables the efficient usage of SCs resources under low traffic conditions. Our framework motivates the MNOs to quantify their tolerance about requesting fewer resources and form the different levels of bids. We show that the proposed auction-based scheme has two desirable properties: 1) truthfulness; and 2) individual rationality. The mechanism is designed based on a multiobjective framework, where the conflicting interests of the involved parties are considered, to provide the optimal solution that maximizes the economic profit of both the third party and the MNOs and minimizes the network energy consumption at the same time.
3) *Performance Evaluation*: We validate the theoretical analysis of the multiobjective problem by computing the Pareto front (i.e., the set of optimal) solutions and assess the effectiveness of the proposed auction-based switching-off algorithm. The analytical and simulation results indicate the potential energy efficiency and economic gains in the network and give the necessary insights to the MNOs to decide whether it is beneficial to enter in a resource allocation negotiation with the third party.

The remainder of this paper is organized as follows. The system model is described in Section II. In Section III, we introduce the auction-based optimization approach that is used for the BSs' switching-off decision. The performance evaluation is provided in Sections IV and V concludes this paper.

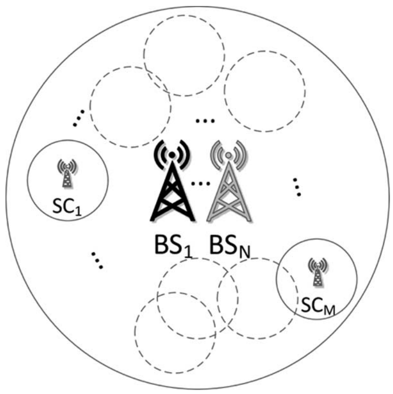


Fig. 1. Network configuration with one macro cell served by N MNOs and covered by M third-party SCs.

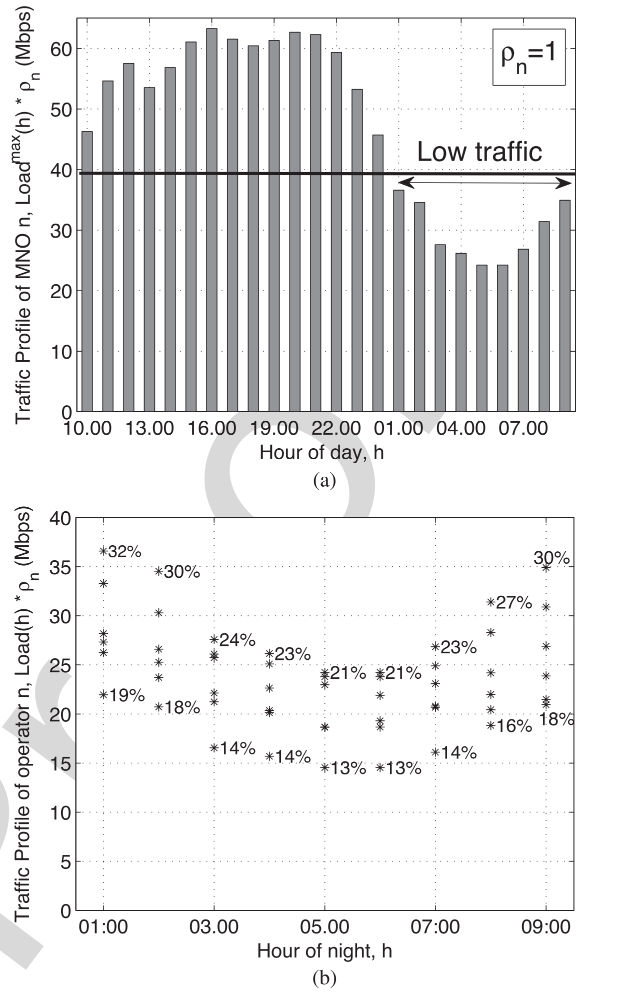


Fig. 2. Traffic pattern scenario and real data traffic values. (a) Traffic load during the 24-hour day. (b) Real data for traffic load patterns.

II. System Model and Operation

A. Network Configuration

We consider an urban scenario, focusing on an area of a macro cell. In the macro cell, we assume that N MNOs provide coverage through their BSs, which are denoted by BS_n, where $n \in \mathcal{N} = \{1, \ldots, N\}$ characterizes the MNO_n. Let us highlight that, in dense networks, due to legal regulations, MNOs are obligated to install their antennas and BSs on the same buildings; thus, we examine networks with collocated BSs [18]. Moreover, in the macro cell, SCs, owned by a third party, are randomly distributed. Each SC is represented as SC_m, where $m \in \mathcal{M} = \{1, \ldots, M\}$. We assume that the number of SCs is adequate to cover the area of the macro cell [19]. As it will be explained in the following, the MNOs are motivated to offload their traffic to the third-party SCs by paying the corresponding price, thus enabling part of BS infrastructure to be switched off during low traffic conditions. The network configuration is shown in Fig. 1.

B. Traffic Load Model

In this paper, we adopt a realistic traffic pattern [20], [21] that corresponds to the maximum traffic per operator in a given cell. Fig. 2(a) plots the maximum traffic per hour, which is denoted by $\mathrm{Load}^{\max}(h)$, throughout the day.[2] Without loss of generality, we focus on the time zone between 01:00 A.M. and 09:00 A.M., when the traffic per BS is relatively low (i.e., less than 40 Mb/s, which corresponds to 35% of the cell's capacity). The selection of the night zone may vary according to the traffic variations, and our algorithm can be adapted to different traffic conditions. In addition, we assume that the traffic volumes of different MNOs may be different, although they follow the same pattern. Hence, we define $\rho_n \in [0, 1]$ as the percentage of each operator's traffic load with respect to the maximum traffic for the respective hour. In this paper, we have used traffic data sets that include information of one operator for ten BSs during the period of one year, thus including weekends, weekdays, and day and night hours. To that end, the reports consists of various values for both low and high traffic. Provided that the data sets had huge information, we classified the days of the year into different periods of time (e.g., seasons, weekdays, and weekends). Based on these real traffic reports and by using simple statistical analysis, we have obtained the necessary insights about the minimum, maximum, and average values of the traffic load, and we have plotted some indicative numbers in Fig. 2(b). Each one of the six values corresponds to the average traffic that was observed in different days during the year. In addition, we express the BS utilization as a percentage of the total BS's capacity resources for the extreme cases of minimum and maximum traffic loads. The two values, i.e., $\mathrm{Load}^{\min}$ and $\mathrm{Load}^{\max}$, are very critical, and it is very important for the MNOs to be able to predict them.

Unlike the existing works in the literature, where each MNO places only one bid corresponding to the maximum capacity requirements, in this paper, we propose that the MNOs place multiple bids corresponding to different levels of the predicted traffic load, as shown in Fig. 2(b). Thus, given the estimated minimum and maximum traffic load levels and assuming that the actual traffic values will, most probably, lie between these extreme values, we are able to calculate different levels of traffic. In this paper, we consider $L + 1$ different traffic load levels. The number of levels depends on the MNOs' strategy

[2]The parameter h can be dropped for the sake of simplicity.

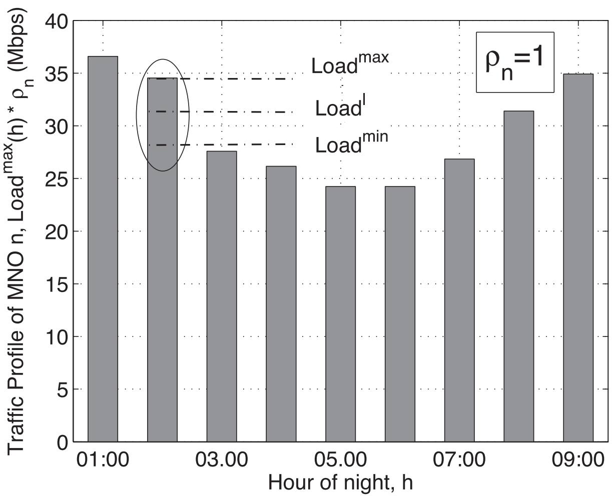


Fig. 3. Traffic during the night zone and different levels of traffic estimation.

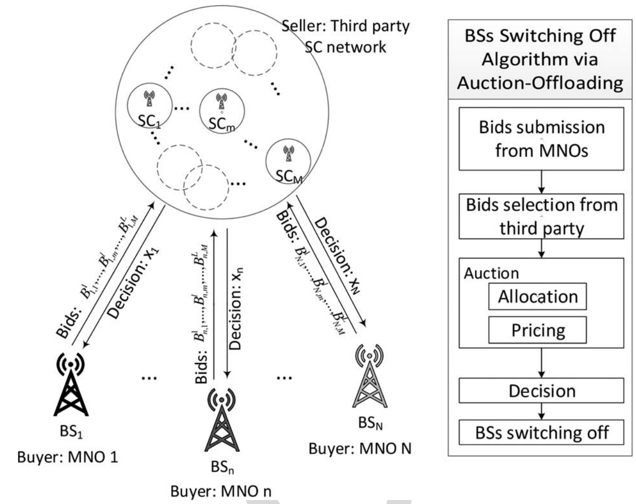


Fig. 4. Auction illustration and proposed algorithm flowchart.

that will be further explained in the following. Each level $l \in \mathcal{L} = \{0, \ldots, L\}$ corresponds to traffic that is equal to

$$\begin{aligned}\mathrm{Load}^l &= \mathrm{Load}^{\min} + \frac{\mathrm{Load}^{\max} - \mathrm{Load}^{\min}}{L} \cdot l \\ &= \left(1 - \frac{l}{L}\right) \cdot \mathrm{Load}^{\min} + \frac{l}{L} \cdot \mathrm{Load}^{\max}. \end{aligned} \tag{1}$$

Evidently, the two extreme values are $\mathrm{Load}^0 = \mathrm{Load}^{\min}$ and $\mathrm{Load}^L = \mathrm{Load}^{\max}$. Fig. 3 shows an example, depicting various traffic levels for a specific hour ($\mathrm{h} = 02{:}00$ A.M.). Based on the above, Appendix A of the supplemental file provides a theoretical estimation of the traffic that can be offloaded, explaining the process of mapping the users of the MNOs to the capacity of the SCs.

III. Auction-Based Switching-Off Algorithm

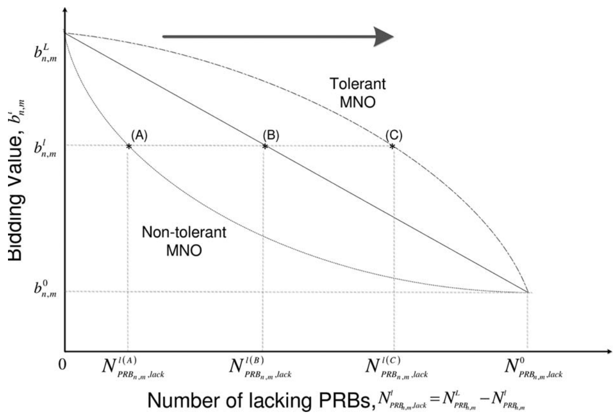
Here, we present the combinatorial auction employed to select the MNOs that can offload their traffic to the SCs, thus being able to switch off their BSs. We provide the bidding strategy, and we formulate the integer linear programming model, which ensures the optimal allocation and the switching-off strategy for the auction. In addition, to ensure truthful bidding, the Vickrey—Clarke—Grooves (VCG) payment mechanism [22] is employed.

A. Big Picture

By considering the limited capacity of the SCs and the MNOs' incentive to switch off their BSs, we use an auction-based mechanism to motivate the operators to offload the traffic to the third-party SC network. Fig. 4 illustrates the main idea of the scheme. In our proposal, both the MNOs and the third party take part in the decision process, each one having a separate role in the framework. On one hand, the MNOs act as buyers, who are willing to lease the SCs resources and opportunistically offload their traffic. On the other hand, the third party, acting as a seller, collects the bids, and through an auction, the subset of MNOs that can offload their traffic, is selected. The proposed auction-based switching-off scheme consists of three main steps: bidding, allocation, and pricing, whose process and the respective decision-makers (in parenthesis) are presented as follows. First, in the *bidding phase* (MNOs), the MNOs place their bids to the third party according to the different values of the requested bandwidth. Each bid includes the information of the requested capacity and the corresponding price that the MNO is willing to offer. Second, in the *allocation step* (third party and MNOs), the third party collects the MNOs' bids. The selection of the optimal resource allocation can be derived through the solution of the resource-allocation problem. Third, in the *pricing step* (third party), the third party decides each winner's payment price, based on the resource allocation of the previous step. The winning MNOs offload their whole traffic to the SCs and switch off their BSs, whereas the losing bidders keep their BSs active.

B. Bidding Strategy

Each SC_m of the third party (seller) has unexploited capacity resources that is willing to lease to the MNOs. The MNOs (buyers) want to offload their traffic to the SCs by requesting specific capacity resources to lease, based on the predictions of the traffic load. The number of the physical resource blocks (PRBs) is calculated in Appendix A of the supplementary AQ1 file. The MNOs valuate the requested resource $N^l_{\mathrm{PRB}_{n,m}}$ at a given price $u^l_{n,m}$, unknown to the third party and the other bidders, where l is the level of resources, $n \in \mathcal{N}$ refers to the corresponding operator, and $m \in \mathcal{M}$ corresponds to the specific SC that the MNO wants to lease the resources from. In the proposed auction-based scheme, each operator submits a set of bid pairs $B^l_{n,m} = (b^l_{n,m}, N^l_{\mathrm{PRB}_{n,m}})$, representing the price $b^l_{n,m} \leq u^l_{n,m}$, which the nth MNO pays for leasing the capacity $N^l_{\mathrm{PRB}_{n,m}}$ from the mth SC. In general, these two values (i.e., $b^l_{n,m}, u^l_{n,m}$) may not necessarily be the same. However, in a truthful auction such as the one that we have (the truthfulness property of the auction will be explained in Section III-D), it is proved that the private valuation and the bidding price are equal; thus, $b^l_{n,m} = u^l_{n,m}$ [5], [6]. After the reception bid pairs, the selection of the subset of the MNOs, whose traffic can be offloaded to the corresponding SCs, follows.



AQ2 Fig. 5. Bidding strategy versus tolerance function.

To gain further insights on the bidding strategy, let us consider the following example. Given the predicted expectations about the traffic, each MNO m submits multiple bids, $b^0_{n,m}, b^1_{n,m}, \ldots, b^l_{n,m}, \ldots, b^L_{n,m}$, indicating the offered price for the requested number of PRBs. Through the different bid pairs, the MNOs actually reveal their outage probability tolerance. In particular, by leasing the maximum calculated number of PRBs ($N^L_{\mathrm{PRB}_{n,m}}$) for the highest bid $b^L_{n,m}$, the MNOs guarantee service to all their users. Controversially, by obtaining a smaller number of PRBs (e.g., $N^l_{\mathrm{PRB}_{n,m}}$ with $l < L$), the MNO pays a smaller price at a risk of leaving some users in outage. The minimum number of requested PRBs $N^0_{\mathrm{PRB}_{n,m}}$ constitutes an upper bound of the operator's outage tolerance. Another parameter determined by each MNO is the number of levels. A higher number of levels results in more bid pairs, thus increasing the performance of the auction while inducing more communication overhead and higher computational complexity.

To flexibly model the MNOs' outage tolerance, we introduce a satisfaction function that represents the bidding value (which is equal to the valuation price) that the MNO is willing to pay for leasing a specific bandwidth. To that end, we define the number of lacking PRBs as the difference between the maximum number of PRBs minus the actually obtained PRBs allocated the MNO, given by

$$N^l_{\mathrm{PRB}_{n,m},\mathrm{lack}} = N^L_{\mathrm{PRB}_{n,m}} - N^l_{\mathrm{PRB}_{n,m}}. \tag{2}$$

The satisfaction function is determined by the requested capacity of each MNO and is monotonically decreasing with the number of lacking PRBs. We also consider that, for each MNO, there is a lower bound for the minimum number of requested PRBs, which minimizes the MNO's satisfaction. This bound indicates that for fewer PRBs the MNO will not participate in the auction. Fig. 5 shows three examples of the outage tolerance function. Three bidding values are emphasized in the plot: The highest bid $b^L_{n,m}$, corresponding to the maximum requested capacity $N^L_{\mathrm{PRB}_{n,m}}$ (with $N^l_{\mathrm{PRB}_{n,m},\mathrm{lack}} = 0$), the lowest bid $b^0_{n,m}$, and an intermediate value $b^l_{n,m}$. As the number of lacking PRBs increases (depicted by the arrow direction in Fig. 5), the bid values decrease, and as a consequence, losses in terms of the served users may be observed. If the number of lacking PRBs exceeds $N^0_{\mathrm{PRB}_{n,m},\mathrm{lack}}$, the MNO will not participate in the auction; thus, no bid lower than $b^0_{n,m}$ will be submitted. The three points (A, B, and C) marked in Fig. 5 correspond to the different tolerance functions of three operators. An outage-tolerant MNO (point C) requests for less bandwidth for the same bidding value $b^l_{n,m}$ compared with a nontolerant MNO (point A) that still requests high capacity from the third party. Hence, the nontolerant MNO places higher priority on guaranteeing user service, whereas the outage-tolerant MNO is willing to sacrifice some resources to increase its probability of winning the auction and switching off its BS, thus enhancing energy efficiency. Finally, point B corresponds to an intermediate bidding strategy defined by a linear function between the two examined parameters.

The user outage tolerance function (keeping in mind that $b^l_{n,m} = u^l_{n,m}$) is modeled as[3]

$$b^l_{n,m} = b^L_{n,m} - \frac{b^L_{n,m} - b^0_{n,m}}{N^L_{\mathrm{PRB}_{n,m}} - N^0_{\mathrm{PRB}_{n,m}}} \cdot \left(N^l_{\mathrm{PRB}_{n,m}}\right)^{\delta}. \tag{3}$$

The distinctive cases for the satisfaction curves are as follows.

- *Nontolerant MNO (Point A)*: For the nontolerant MNO, the outage tolerance function is convex, with $\delta < 1$.
- *Average-tolerant MNO (Point B)*. There is a linear relation between the bidding strategies and the outage tolerance of the MNOs, by substituting $\delta = 1$ in (3).
- *Tolerant MNO (Point C)*. For the tolerant MNO, the satisfaction function is concave, with $\delta > 1$.

The parameter δ may obtain a wide range of values. The selection of a value equal to $\delta \ll 1$ corresponds to a strictly nontolerant MNO, who decreases its bid requests very fast. In contrast, a very high value of this indicative parameter (i.e., $\delta \gg 1$) would lead to very slowly decreasing bidding values and, thus, to a very tolerant operator.

C. Auction Formulation

By employing the properties of combinatorial auction theory, we formulate the problem of the opportunistic offloading as an auction. Each MNO $n \in \mathcal{N}$ places the corresponding bid pairs $B^l_{n,m}$. Having received the bids, the third party selects the subset of MNOs that maximizes the desired goals of all the involved participants. We define $x^l_{n,m}$ as a binary decision variable that indicates whether the corresponding bidder (MNO n) is winner ($x^l_{n,m} = 1$) or not ($x^l_{n,m} = 0$) in the corresponding SC$_m$ and for the lth bidding value.

The cost of using the SC infrastructure and the increased consumed energy are the main objectives: the maximization of the profits (the economic objectives of the third party and the MNOs) and the minimization of the energy consumption (the energy objective). In continuation, a detailed analysis of the objectives of each party is presented.

1) Third Party's Objective: The third party aims at *maximizing its profit* by leasing high volumes of the capacity of SCs at

[3]The values of $b^0_{n,m}$ and $b^L_{n,m}$ will be calculated in details in the succeeding section, where the constraints and requirements posed by the MNOs and the third party are given within the optimization framework.

increased prices. The profit is defined as the difference of the MNOs' winning bids minus its expenses (CapEx and OpEx). We define the financial gain of the SC network $\mathrm{CG_{SC}}$ as

$$f_1(\mathbf{x}) = \mathrm{CG_{SC}} = \sum_{n\in\mathcal{N}} \sum_{m\in\mathcal{M}} \sum_{l\in\mathcal{L}} x_{n,m}^{l} \cdot b_{n,m}^{l} - M \cdot C_{\mathrm{SC}} \quad (4)$$

where C_{SC} is the cost of a SC, corresponding to the sum of its CapEx and the traffic-dependent OpEx. For the calculation of the SCs cost, the cost model presented in [23] is employed.

To ensure its objective, the third party introduces a minimum profit, which is described as a function of its total cost, i.e.,

$$\mathrm{CG_{SC}^{min}} = y \cdot M \cdot C_{\mathrm{SC}}, \quad y > 0. \quad (5)$$

Given the minimum profit, which is calculated by (5), we estimate the reservation price as follows.

Proposition 1: The reservation price is defined as the minimum price that a seller would be willing to accept for leasing the corresponding bandwidth, i.e.,

$$b_{\mathrm{res},n,m}^{l} = \frac{N_{\mathrm{PRB}_{n,m}}^{l}}{N_{\mathrm{PRB}}^{\max}} \cdot y \cdot M \cdot C_{\mathrm{SC}}. \quad (6)$$

Proof: The third party is willing to share its resources among the MNOs based on proportional fairness by ensuring that a minimum profit gain will be achieved, at the same time. To that end, it calculates a reservation price, which is the minimum price that the third party will accept from an MNO to lease a specific bandwidth. The maximum number of PRBs that the nth MNO can offload to the mth SC is given by

$$N_{\mathrm{PRB}_{n,m}}^{l} = \frac{b_{\mathrm{res},n,m}^{l} \cdot x_{n,m}^{l}}{\sum_{n\in\mathcal{N}} \sum_{l\in\mathcal{L}} b_{\mathrm{res},n,m}^{l} \cdot x_{n,m}^{l}} \cdot N_{\mathrm{PRB}}^{\max}. \quad (7)$$

Finally, by using (5) and (7) in (4), the reservation price for offloading traffic is calculated. ■

The reservation price in (6) is not the price that the MNOs will propose to lease their requested capacity, although it is a threshold price that the third party uses to eliminate all the offers that are less than the accepted. The reservation price can be either announced or unknown to the MNOs. The reservation price means that the seller would rather withhold the capacity if the proposed bids are too low (i.e., lower than the reservation price), and given this price, the auction process can be accelerated since the set of prices that are lower than the reservation price can be discarded.

2) MNOs' Objective: The objective of each MNO is the *maximization of its financial profits*. The maximization of the profits of the nth MNO is defined as the revenue from switching off its BS minus the winning bids for leasing the requested capacity from the third party. Therefore, the profit (cost gain) can be written as

$$f_2(\mathbf{x}) = \mathrm{CG}_n = C_{\mathrm{BS}} \cdot x_n - \sum_{m\in\mathcal{M}} \sum_{l\in\mathcal{L}} x_{n,m}^{l} \cdot b_{n,m}^{l} \quad (8)$$

with

$$x_n = \prod_{m\in\mathcal{M}} \sum_{l\in\mathcal{L}} x_{n,m}^{l} \quad \forall\, n \in \mathcal{N} \quad (9)$$

and C_{BS} being the cost of a BS, whose model is also presented in [23], provided that

$$\sum_{l\in\mathcal{L}} x_{n,m}^{l} \in \{0,1\} \quad \forall\, n \in \mathcal{N} \quad \forall\, l \in \mathcal{L}. \quad (10)$$

At this point, let us recall that an operator is able to switch off its BS if it wins in an auction in all the SCs, a condition that is represented by the product in (9). The product is equal to 1 only when the nth MNO wins in M auctions in respective SCs; otherwise, it is 0.

The MNOs are willing to participate in the auction and lease bandwidth resources from a third party if they guarantee a minimum profit gain. Consequently, they introduce a minimum profit, which is described as a percentage of their total costs, i.e.,

$$\mathrm{CG}_n^{\min} = z \cdot C_{\mathrm{BS}}, \quad 0 < z < 1. \quad (11)$$

The bidding strategy of the MNOs, along with the proposed bids, depend on the minimum profit gain and the operation costs of the BSs. However, the cost gain can be attained if and only if the nth MNO wins in M auctions and is able to lease the requested capacity. In addition, since we consider uniform traffic in the macro cell, we conclude that the bids in the different SCs must be equal and proportional to the corresponding traffic. Thus, the maximum bid price for offloading the traffic in the mth cell is calculated as

$$b_{n,m}^{L} = \frac{(1-z) \cdot C_{\mathrm{BS}}}{M}. \quad (12)$$

Similarly, the minimum bidding price is a proportional value of the maximum one, which is given by

$$b_{n,m}^{0} = v \cdot \frac{(1-z) \cdot C_{\mathrm{BS}}}{M} \quad (13)$$

where $v \in (0,1)$. The bidding values of the remaining $L-1$ levels can be calculated based on (3), depending on the maximum bid value and the relation between the outage tolerance of the MNOs and the discount they can be offered for the lower requested bandwidth.

3) Overall Objective: The overall objective of the network is the *minimization of the energy consumption*. This can be attained by reducing the number of active BSs, given that the BSs are responsible for the major part of energy consumption in the network. The network energy consumption $\mathbb{E}[E]$ is

$$f_3(\mathbf{x}) = \mathbb{E}[E] = \sum_{n\in\mathcal{N}} \mathbb{E}\left[E_{\mathrm{BS}_n}\right] \cdot (1 - x_n) + M \cdot \mathbb{E}[E_{\mathrm{SC}}] \quad (14)$$

where $\mathbb{E}[E_{\mathrm{BS}_n}]$ and $\mathbb{E}[E_{\mathrm{SC}}]$ represent the energy consumption of BS and SC, respectively.

The combinatorial auction formulation should include all the objectives of the participating entities. To capture the trade-off between the objectives, the multiobjective optimization [24] is employed. The target is to find a subset of acceptable solutions according to a set of objectives. In general terms, the objectives may be conflicting, and consequently, a single global optimum may not exist. Hence, the notion of an optimum set $\mathbf{x}^*$ becomes very important. Some relevant definitions are given in the following.

Definition 1: Given the three objectives, $f_1(\mathbf{x})$, $f_2(\mathbf{x})$, and $f_3(\mathbf{x})$, and provided that $\mathbf{x}_1$ and $\mathbf{x}_2$ are two decision variables, then $\mathbf{x}_1$ is said to be the Pareto dominant, and is denoted $\mathbf{x}_1 \succeq \mathbf{x}_2$ if and only if $f_i(\mathbf{x}_1) \geq f_i(\mathbf{x}_2)\, \forall\, i \in \{1, 2, 3\}$, and $f_j(\mathbf{x}_1) > f_j(\mathbf{x}_2)$, for at least one index $j \in \{1, 2, 3\}$.

Definition 2: $\mathbf{x}^*$ is said to be Pareto optimal (or nondominated), if there is no other $\mathbf{x}$, so that $\mathbf{x}$ dominates $\mathbf{x}^*$. The set of all Pareto solutions in the decision space is called the Pareto optimal set and the image of the Pareto optimal set in the objective space is called the Pareto optimal front.

Based on the aforementioned definitions, the ILP multiobjective optimization problem can be formulated as follows.

Definition 3: The allocation problem is to determine the optimal solution $\{x^l_{n,m}\}\ \forall\, n \in \mathcal{N}\ \forall\, m \in \mathcal{M}$, and $\forall\, l \in \mathcal{L}$ that maximizes the distinctive objectives of the involved parties in the auction, subject to capacity and offloading targets

$$\mathbf{P1}:\ \max\ [\mathrm{CG}_{\mathrm{SC}},\ \mathrm{CG}_n,\ -\mathbb{E}[E]] \tag{15}$$

s.t.

$$\sum_{n\in\mathcal{N}}\sum_{l\in\mathcal{L}} x^l_{n,m}\cdot N^l_{\mathrm{PRB}_{n,m}} \leq N^{\max}_{\mathrm{PRB}}\quad \forall\, m \in \mathcal{M} \tag{16}$$

$$\sum_{l\in\mathcal{L}} x^l_{n,m} \in \{0,1\}\quad \forall\, n\in\mathcal{N}\quad \forall\, m\in\mathcal{M} \tag{17}$$

$$b^l_{n,m} \geq b^l_{\mathrm{res},n,m}\quad \forall\, n\in\mathcal{N}\quad \forall\, m\in\mathcal{M}\quad \forall\, l\in\mathcal{L} \tag{18}$$

$$x^l_{n,m} \in \{0,1\}\quad \forall\, n\in\mathcal{N}\quad \forall\, m\in\mathcal{M}\quad \forall\, l\in\mathcal{L}. \tag{19}$$

The constraint in (16) ensures that the total number of allocated resources does not exceed their availability, constraint (17) ensures that only one bid of the nth MNO in the mth SC can be the winning bid among the l different ones, constraint (18) ensures that the bids are higher than the reservation price, and constraint (19) ensures the integrality of the binary variable. The objectives of the proposed optimization formulation are contradictory. The maximization of the third party income does not imply the BSs switching off, whereas the energy objective does not ensure the third party's interests. The maximization of the financial gains of the third party may lead to additional economic losses from the MNOs' perspective since the maximization of this objective may lead to a resource allocation that does not imply the deactivation of BSs.

Exploiting the fact that the BSs are responsible for the major part of the energy consumption, the third objective of the problem $f_3(\mathbf{x})$ can be transformed into a constraint. Energy consumption is minimized when the maximum number of MNOs switches off their BSs after winning in M auctions, a condition represented by the product in (9). Thus, the problem **P1** is transformed into a simpler formulation in (20), and at the same time, the energy consumption objective is not neglected, in contrast to former works [17], where only the maximization of the third party's income is considered. The equivalent problem is as follows:

$$\mathbf{P2}:\ \max\ [\mathrm{CG}_{\mathrm{SC}},\ \mathrm{CG}_n] \tag{20}$$

s.t.

$$\prod_{m\in\mathcal{M}}\sum_{l\in\mathcal{L}} x^l_{n,m} \in \{0,1\}\quad \forall\, n\in\mathcal{N} \tag{21}$$

$$\sum_{n\in\mathcal{N}}\sum_{l\in\mathcal{L}} x^l_{n,m}\cdot N^l_{\mathrm{PRB}_{n,m}} \leq N^{\max}_{\mathrm{PRB}}\quad \forall\, m \in \mathcal{M} \tag{22}$$

$$\sum_{l\in\mathcal{L}} x^l_{n,m} \in \{0,1\}\quad \forall\, n\in\mathcal{N}\quad \forall\, m\in\mathcal{M} \tag{23}$$

$$b^l_{n,m} \geq b^l_{\mathrm{res},n,m}\quad \forall\, n\in\mathcal{N}\quad \forall\, m\in\mathcal{M}\quad \forall\, l\in\mathcal{L} \tag{24}$$

$$x^l_{n,m} \in \{0,1\}\quad \forall\, n\in\mathcal{N}\quad \forall\, m\in\mathcal{M}\quad \forall\, l\in\mathcal{L}. \tag{25}$$

The objective function (20) aims at maximizing the financial gain of both the third party and the MNOs. Constraint (21) ensures that an operator either wins in one auction in the M SCs (and switches off its BS) or loses in all the auctions (keeps its BS active). Thus, this constraint ensures the minimization of the energy consumption given by (14) since the selected resource allocation leads to the highest number of switched-off BSs, while at the same time achieving the increase in MNOs and third party's income. Constraints (22)–(25) are the same as (16)–(19), respectively.

The multiobjective problem **P2** belongs to the class NP-Complete since it is equivalent to the 0–1 knapsack problem, which is a well-known problem in combinatorial optimization. For the NP-hard problems, an optimal solution is difficult to be found due to the large number of variables [24]. However, there are different solutions that represent the best feasible state of the investigated system, e.g., the best resource allocation for the deactivation of the highest number of BSs. To find the best possible representation or a good approximation of these optimal solutions that are widely known as the Pareto optimal set or as the optimal Pareto front and to overcome the high complexity of multiobjective problems, metaheuristic methods (also sometimes called genetics) have become a very active research area, and several algorithms have been proposed [25], [26]. Although, the metaheuristic algorithms do not guarantee that this approximation is the optimal, the solutions are still good and near optimal.[4]

The metaheuristic algorithm that finds the Pareto solution for our multiobjective optimization problem works on a set of possible combinations of the decision variables [24]. The basic definition of the Pareto front is that it consists of exactly those point solutions that are not dominated by any other point. The different objectives cannot be optimized simultaneously. Thus, first, the solutions that maximize the MNOs's income and the third party's economic gains are calculated separately.

[4]For the sake of simplicity, we use the term "Pareto front" throughout this paper to refer to the obtained solutions through metaheuristics.

Obviously, these solutions that maximize the cost gains of the MNOs and the third-party always belong to the Pareto front and, in fact, they are its endpoints. A simple algorithm to find the other solutions (if any) on the Pareto front begins by sorting the solutions according to one of the objectives, e.g., third party's income. The algorithm then starts with the point with the maximum gain for the third party and continues to the successive solutions in order of increasing third party's cost until the solutions with higher cost gain value for the operators is found. This solution is then added to the Pareto front, and the search is restarted from it.

Through the use of metaheuristics, the problem can be solved efficiently and quickly for a relatively small number of MNOs and SCs [25], [27], [28]. This assertion cannot be concluded and generalized for large networks. In the investigated network configuration with 5 MNOs, 15 SCs, and 9 bidding levels, the runtime of the solution is very short. At this point, let us clarify that the numbers selected for the MNOs and the SCs are based on the most typical and realistic scenarios in recent studies [18], [19] since the most common scenarios in European countries involve three to four MNOs, and 15 SCs can cover the service are of one macro BS.

D. Pricing Strategy

Having defined the ILP model, we now illustrate the payment rule, which is of crucial importance for the realization of the auction for the third party. The VCG payment induces all the users to reveal their actual valuations for the requested bandwidth. In the VCG mechanism, the third party charges the bidders (MNOs) with a price for the requested capacity. For example, an MNO who requires large bandwidth will have to pay a high price since its request results in dissatisfying other MNOs who lose in the auction because of the limited capacity resources and will not be able to offload their traffic.

Let us denote by $p^l_{n,m}$ the price paid by the MNO n to the third party for the allocated capacity of the mth SC. The payoff function for bidder n that represents the difference between the gain of the MNO attained through the BS switching off and the true valuation minus the paid price (let us recall that in the truthful auction $u^l_{n,m} = b^l_{n,m}$) is

$$\mathcal{U}_i = \begin{cases} \mathrm{CG}_i + \sum\limits_{m\in\mathcal{M}} \sum\limits_{l\in\mathcal{L}} u^l_{i,m} - \sum\limits_{m\in\mathcal{M}} \sum\limits_{l\in\mathcal{L}} p^l_{i,m}, & \text{if } i \text{ is selected} \\ -C_{\mathrm{BS}}, & \text{otherwise.} \end{cases} \tag{26}$$

The payment rule for each MNO can be defined as follows:

$$p^l_{i,m} = \sum_{n\in\mathcal{N}\setminus\{i\}} \sum_{m\in\mathcal{M}} \sum_{l\in\mathcal{L}} \left(x^l_{i,m}\right)^{\{-i\}} \cdot b^l_{i,m} - \left(\sum_{n\in\mathcal{N}\setminus\{i\}} \sum_{m\in\mathcal{M}} \sum_{l\in\mathcal{L}} x^l_{i,m} \cdot b^l_{i,m} - \sum_{n\in\mathcal{N}\setminus\{i\}} \sum_{m\in\mathcal{M}} \sum_{l\in\mathcal{L}} x^l_{i,m} \cdot b^l_{i,m} \right) \tag{27}$$

TABLE I
SIMULATION PARAMETERS

Parameter	Value	Parameter	Value
Number of MNOs, N	5	BS bandwidth, CR_{BS}	20 MHz
Number of SCs, M	15	SC bandwidth, CR_{SC}	5 MHz
Traffic load, $Load$	Fig. 3	δ	[0.5, 1.5]

where the first term is the aggregate valuation of the allocated resources, $(x^l_{n,m})^{\{-i\}}$, when MNO i does not participate at all in the auction. The second term is the aggregate valuation of the allocation $x^l_{n,m}$ of all MNOs other than i, when i participates in the auction. Next, we prove that our optimized auction mechanism possesses two important properties: 1) truthfulness and 2) individual rationality.

Proposition 2 (Truthfulness): The payment rule defined in (27) satisfies the truthfulness property.

Proof: The proof is given in Appendix B in the supplemental file. ■

Proposition 3 (Individual Rationality): The payment rule defined in (27) satisfies the individual rationality property, and all bidders are guaranteed to obtain nonnegative utility.

Proof: The proof is given in Appendix C in the supplemental file. ■

IV. PERFORMANCE EVALUATION

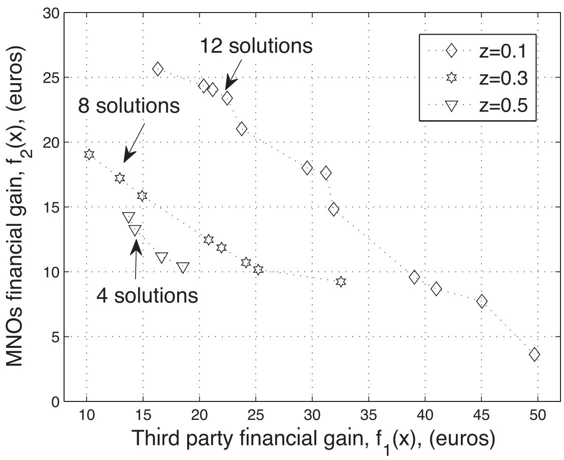
This section is composed of three parts. First, we explain the simulation scenario employed both for the multiobjective optimization and the system-level simulations. Second, we present the results regarding the estimation of the Pareto front for the multiobjective optimization solved by using the Matlab tools. Finally, we show a performance comparison between the proposed scheme and two state-of-the-art schemes with the development of a custom-made C simulator.

A. Simulation Scenario

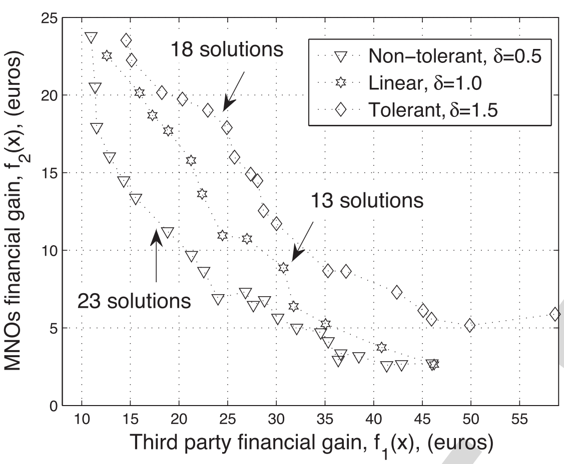
The simulation scenario corresponds to a dense HetNet deployment, such as a university campus or an urban area. More specifically, our scenario focuses on a cell served by the BSs of $N = 5$ MNOs and $M = 15$ SCs that cover the whole cell area. In our experiments, we consider various scenarios, wherein the MNOs have different traffic volumes (i.e., ρ), different bidding strategies (i.e., nontolerant, linear, and tolerant), different cost requirements (i.e., z), and different bidding levels (i.e., L). The system-level simulations are based on Monte Carlo experiments, and the presented results focus on the night zone for the duration of one year.[5] The set of parameters is provided in Table I.

To assess the performance of our scheme, we compare the proposed multiobjective auction-base switching-off strategy (referred to as MAS), to two benchmark solutions: 1) an auction-based switching-off scheme, wherein the income of the

[5]Note that the results are calculated for the case of one macro cell, but they can be easily extended to extended configurations. Furthermore, we consider the period of one year since the yearly traffic is considered stable [30].



(a)



(b)

AQ4 Fig. 6. Estimation of Pareto front solutions. (a) Estimated Pareto front for multiple MNOs' requirements, $L = 2$ and linear bidding strategy. (b) Estimated Pareto front for multiple bidding strategies, $L = 2$, and $z = 0.1$.

third party is the unique objective to be maximized (referred as ISO) [17]; and 2) a baseline scenario with full operational topology (FOT), where none of the BSs is switched off.

B. Estimation of the Pareto Front

Here, we present the Pareto front analysis. In this set of experiments, we assume that all operators have the same traffic volume equal to the maximum possible traffic load, i.e., $\rho_n = 1$. In addition, we assume that each MNO submits three different bids, corresponding to $L = 2$, to the third party.

Fig. 6 shows the Pareto front solutions achieved by solving the proposed multiobjective problem for different minimum financial gains with the same bidding strategy [see Fig. 6(a)] and different bidding strategies with the same minimum profit requirement [see Fig. 6(b)]. In both figures, the third party's annual financial gain that can be attained by leasing its resources to one MNO is represented in the x-axis, and the annual economic profits of one MNO are given in y-axis.

In Fig. 6(a), the set of optimal solutions is shown for the linear bidding strategy. Note that the stochastic search performed by means of the metaheuristic algorithm succeeds in estimating a Pareto front for the given parameters of the studied problem. As expected, in all the different cases, the higher the third party's income $(f_1(\mathbf{x}))$, the lower the financial gain of the MNOs $(f_2(\mathbf{x}))$. Thus, the Pareto front is monotonically decreasing, meaning that the improvement of one objective leads to the deterioration of the other objective, and there is no feasible global solution maximizing all the objectives. A second observation relies on the motivation of the MNOs to maximize their economic gains, which is a fact that can be explored through the parameter z that reflects the requirements of the minimum profit gain, denoted in (11). As it is plotted in the figure, the greedy behavior of the MNOs for higher cost gains $(z = 0.5)$ leads to lower income for the third party and, at the same time, a lower number of achievable solutions. This result is of significant importance since a greedy behavior from the MNOs' perspective will produce lower bids that may not be accepted by the third party; thus, the MNOs will not be able to offload their whole traffic. The selection of a proper value of the parameter z helps the operators to decide whether it is profitable for them to bid by taking into account their financial needs, and by observing Fig. 6(a), we conclude that lower values of z lead to higher income for the two involved parties. To provide further insights for our approach, let us also highlight that, in a realistic scenario with a large number of macro BSs, the cost gains for the MNOs and the third party are significantly higher. For example, by applying the proposed switching off technique to the central area of London where an MNO may have up to 500 deployed BSs [31], the economic gains may reach up to ∼12.500 € for the MNO and up to ∼25.000 € for the third party.

In continuation, Fig. 6(b) illustrates the Pareto front by examining different bidding strategies for the case of $z = 0.1$. Again, we observe that the attained solutions are decreasing monotonically. Moreover, as we see, the more tolerant the bidding strategy of the MNOs, the higher financial gains for the involved parties. This important insight can be easily explained by taking into account the fact that a nontolerant MNO is more greedy; thus, it requests more capacity for the same bids with respect to a tolerant MNO, as shown in Fig. 5. As a result, the third party may lose its incentive to lease the bandwidth, and the economic benefits will be reduced for the MNOs and the SC network. It is noted that the tolerant bidding strategy offers better solutions due to the leasing of more resources and the switching off of higher number of BSs, whereas the linear bidding strategy implies an intermediate solution between the extreme cases. Hence, along with the minimum guaranteed profit, the bidding strategy is also an important indicator that affects the decision of MNOs on bidding.

C. Numerical Results

Here, the performance results with regard to telecommunication-oriented (network throughput and energy efficiency) and cost-oriented (annual cost and income gains) metrics are shown. In this set of experiments, we study a more realistic scenario, where the MNOs have different traffic volumes and, thus, different requirements and outcomes, when our proposed algorithm is applied. According to recent studies

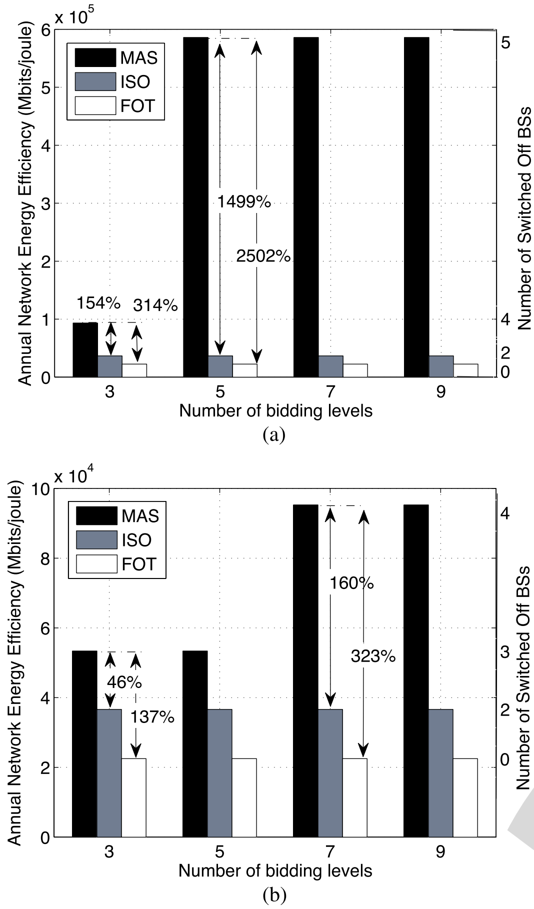


Fig. 7. Annual energy efficiency for $z = 0.1$ and different bidding strategies. (a) Tolerant bidding strategy. (b) Nontolerant bidding strategy.

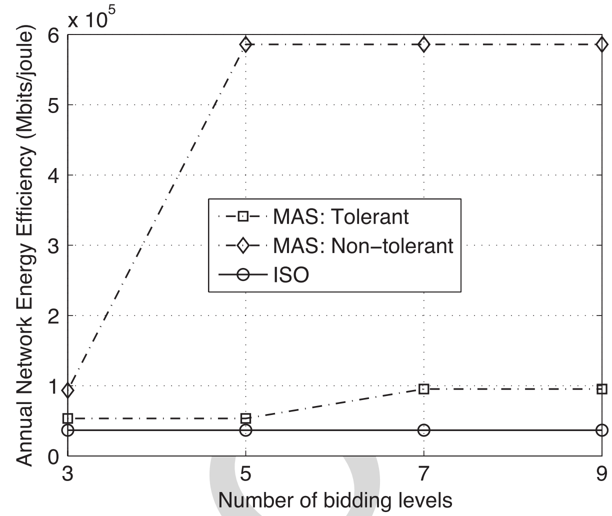


Fig. 8. Annual energy efficiency for different bidding levels and strategies.

[18], in most European countries, there are usually up to two telecommunication companies holding the major part of the market share, up to two smaller operators serving an intermediate portion of the users, and finally, up to one smaller MNO with a very small slice of the market. By exploiting these interesting findings, we consider the scenario in which two MNOs (i.e., BS_1 and BS_2) are fully loaded ($\rho_1 = \rho_2 = 1.0$), two operators (i.e., BS_3 and BS_4) have relatively lower traffic with $\rho_3 = \rho_4 = 0.7$, and the fifth MNO (denoted by BS_5) has very low traffic ($\rho_5 = 0.3$). The results presented in the following are calculated for an operating point on the Pareto front that is assumed to satisfy all the involved parties in the auction. We would like to highlight that the selection of a solution among the Pareto front solutions can be either derived through agreements between the involved parties or another distinguished entity may select it.

1) Telecommunication Metrics: Fig. 7 presents the total network energy efficiency versus L for tolerant [see Fig. 7(a)] and nontolerant [see Fig. 7(b)] bidding strategies. The number of switched-off BSs of every algorithm is also shown in the plot (right y-axis), along with the percentage gains in terms of energy efficiency of our approach compared with the state-of-the-art works. First, we observe that the energy efficiency achieved by the MAS scheme increases with the number of levels for tolerant and nontolerant bidding since the biggest variety of the proposed bids (higher number of levels) implies a higher number of choices for the resource allocation. Another important remark is that MAS significantly outperforms the baseline scenario, FOT, (where no BS is switched off), and the ISO algorithm. The better performance of our proposal in terms of energy efficiency is justified by the higher number of switched-off BSs as this is highlighted also in the plots. As we have already mentioned in Section III-C, the goal of our proposal lies in maximizing the energy efficiency, an objective neglected in the auction-based works of the literature, whereby only the maximization of the third party's income was considered. Comparing the behavior of our algorithm in the two figures, it can be observed that the tolerant bidding strategy achieves more considerable gains with respect to the nontolerant bidding, mainly due to the deactivation of many underutilized BSs in the network. These results emphasize the role of the bidding strategy and the number of bidding levels on the achievable energy efficiency, thus providing the necessary insights to the MNOs to select the most appropriate strategy based on their interests. In Fig. 8, the conclusions of Fig. 7(b) and (a) are better illustrated since the comparison between the three schemes and the different bidding strategies is more clearly shown. Finally, we should mention that the results of linear bidding are not shown here for simplicity, given that the achieved gains range between the two aforementioned cases.

Along with the total network energy efficiency performance, it is interesting to study the individual energy efficiency gains of the different MNOs. To that end, the individual gains for the specific (but representative) case of $z = 0.1$ and the two different bidding strategies are quantified in Table II, where interesting conclusions can be extracted. In particular, independently of the bidding strategy and the number of L, the ISO scheme is beneficial only for the group of operators that switch off their BSs, who are always the same (MNO_1 and MNO_2), whereas the rest of the operators always keep their BSs active. More specifically, the MNOs that switch off their BSs theoretically achieve infinite energy efficiency, as they

TABLE II
OPERATOR ENERGY EFFICIENCY (X 10^4 Mbits/Joule) WITH RESPECT TO THE FOT SCHEME FOR $z = 0.1$

	Tolerant bidding					Non-tolerant bidding				
Algorithm	MNO_1	MNO_2	MNO_3	MNO_4	MNO_5	MNO_1	MNO_2	MNO_3	MNO_4	MNO_5
MAS-L = 3	∞	3	∞	∞	∞	∞	3	2.2	∞	∞
ISO-L = 3	∞	∞	2.2	2.2	1	∞	∞	2.2	2.2	1
MAS-L = 7	∞	∞	∞	∞	∞	∞	3	∞	∞	∞
ISO-L = 7	∞	∞	2.2	2.2	1	∞	∞	2.2	2.2	1

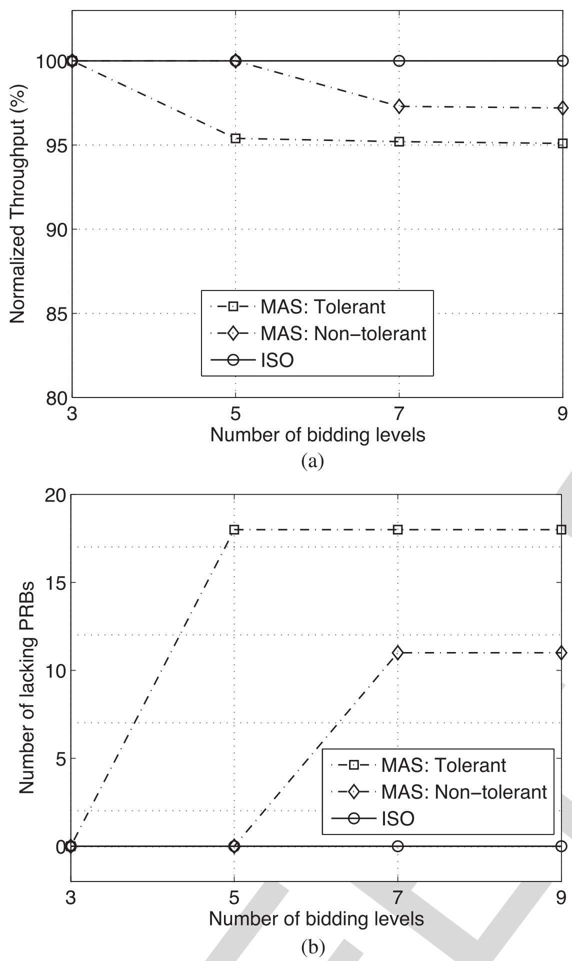


Fig. 9. (a) Normalized throughput for different bidding levels and strategies. (b) Number of lacking PRBs.

have their traffic served at zero energy cost, whereas the active operators serve their own traffic without improving their situation. The proposed MAS eliminates this unfairness by offering the chance to more MNOs to switch off their BSs, providing them with extra incentives to participate in the auction. The individual gains are remarkable of our proposal for both the MNOs and the whole network.

Despite the importance of the energy efficiency results, the deactivation of the BSs in the network and the traffic offloading to the SCs potentially implies loss of connections. To that end, we study the normalized throughput that represents the percentage of served connections in the system. In Fig. 9(a), it can be observed that, as the number of switched-off BSs increases, the MAS approach experiences small losses (around 5% and 3% for tolerant and nontolerant bidding, respectively). The degraded performance is explained by the high number of deactivated BSs, leading to the service of all the traffic mainly by the SC network (since at most one BS remains active). The MNOs are able to decide whether the throughput performance can be sacrificed to achieve energy efficiency, or even small losses are prohibitive (thus, a tolerant strategy is not acceptable). The results in terms of lacking PRBs are given in Fig. 9(b). As it is observed, a larger number of PRBs are lacking, when the MAS strategy is applied. In our case, there are different reasons for the degraded throughput performance. The unserved users exist because either lower bids (thus, fewer PRBs) are selected or the overall PRBs are not adequate for the total offloaded traffic. However, the impact on the throughput is negligible, as it was shown in Fig. 9(a).

2) Cost Metrics: The total annual network cost and the individual annual gains for the operators and the third party, compared with the state-of-the-art algorithm and having as a benchmark the FOT scheme, are presented in Figs. 10 and 12, respectively.

The annual network cost is given versus the different number of bidding levels and for the tolerant [see Fig. 10(a)] and nontolerant [see Fig. 10(b)] bidding strategies, respectively. The total network cost is the sum of the average cost of all MNOs and the third party for the operation of all infrastructures (i.e., the active BSs and SCs). The first observation is that the network cost is the same for level pairs ($l = 3$ and $l = 5$) and ($l = 7$ and $l = 9$) for the MAS algorithm, due to the number of switched-off BSs that is the same for the two cases. The MAS scheme achieves a considerable reduction up to 94% and 96% for tolerant bidding, when compared with ISO and FOT schemes, respectively. For the case of nontolerant bidding strategy, the cost reduction is lower. This result is explained by the fact that MNOs are more greedy, and in their attempt to increase their economic gains, they do not offer high bids for the requested capacity. As a consequence, the third party does not accept the allocation of resources to low prices, and some BSs may not be switched off. Concerning the ISO scheme, we observe that the total annual cost is not affected by the different bidding levels since, in ISO auction, only one bid is offered based on the maximum traffic expectations, and fewer BSs are deactivated. A clear comparison between MAS, for tolerant and nontolerant bidding, and ISO is given in Fig. 11, where the annual network cost behavior is highlighted.

The individual revenue of each MNO and the third party is plotted in Fig. 12. We may observe that, similar to the energy efficiency gains, the ISO scheme provides financial gains only to particular operators (MNO_1 and MNO_2) and particularly to

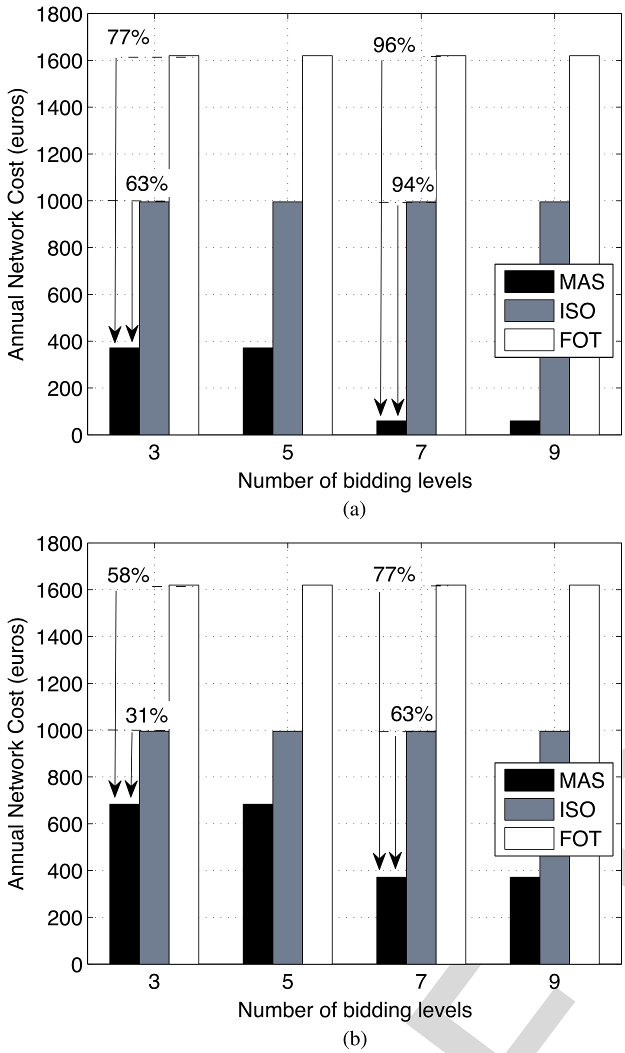


Fig. 10. Annual network cost for $z = 0.1$ and different bidding strategies. (a) Tolerant bidding strategy. (b) Nontolerant bidding strategy.

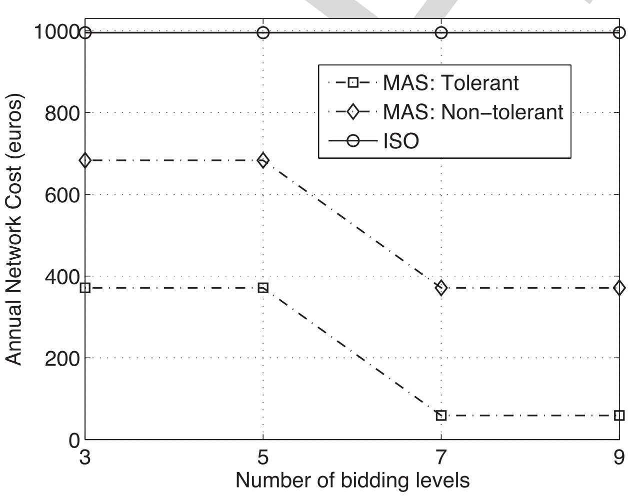


Fig. 11. Annual network cost for different bidding levels and strategies.

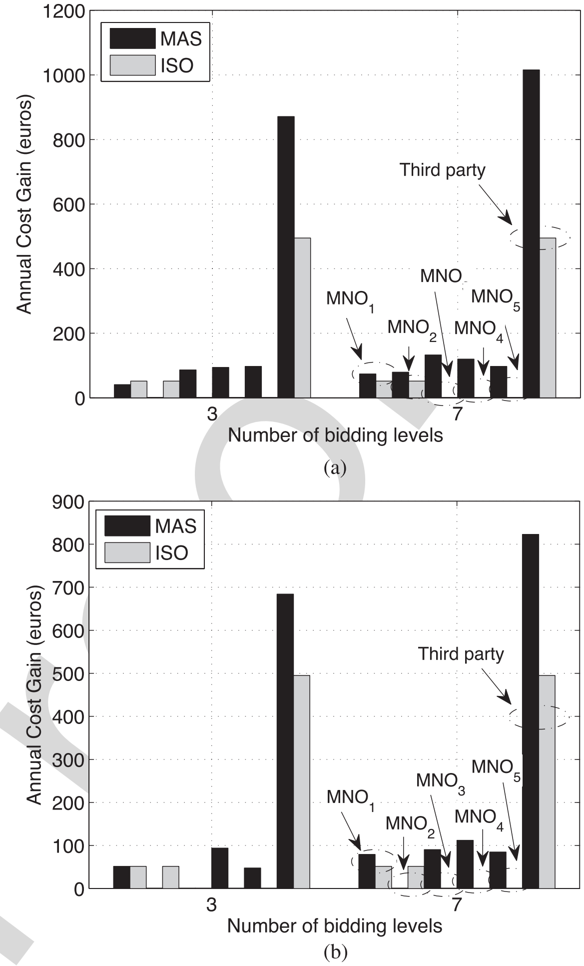


Fig. 12. Annual cost gain for $z = 0.1$ and different bidding strategies. (a) Tolerant bidding strategy. (b) Nontolerant bidding strategy.

the MNOs that switch off their networks, whereas the economic gains of the remaining operators are zero compared with the FOT scheme since these MNOs keep their BSs active and serve their own traffic without having any benefit from the auction. On the other hand, for the proposed MAS approach, more operators are able to have economic benefits, independently of the particular number of levels. Furthermore, as the number of bidding levels increases, the MAS algorithm achieves higher financial gains for the operators due to the higher number of combinations of bids offered. In addition, for the tolerant bidding strategy [see Fig. 12(a)], the economic gains are higher compared with the nontolerant behavior [see Fig. 12(b)].

D. Discussion

Based on the analysis in Sections IV-B and IV-C, we have shown that the proposed MAS scheme outperforms the state-of-the-art approaches in terms of energy efficiency (network and individual), annual network cost, and individual cost gains. In addition, it achieves balanced results for the MNOs with respect to the individual energy efficiency and cost gains. Furthermore, through a performance assessment, we have identified the significance of the bidding behavior, the number of levels, and parameter z. In particular, better performance results are attained in terms of energy efficiency, aggregate network cost, and individual cost gains, when a higher number of levels are chosen and through tolerant bidding. Moreover, higher values of z achieve lower gains for both the MNOs and the third party. Finally, although minor losses may appear in terms of throughput, the attained benefits with respect to energy efficiency, individual and network cost gains are remarkable and are adequate for giving the necessary incentives to the MNOs and the third party to apply the proposed auction-based switching-off strategy.

V. Conclusion

In this paper, motivated by the low BS utilization during the night and the coexistence of multiple MNOs and third-party SCs in the same area, we proposed a novel auction-based offloading and switching-off algorithm that achieves energy savings and cost reduction by encouraging MNOs to offload their traffic and switch off the redundant BSs. Moreover, by employing auction tools and novel bidding strategies, we introduced a switching-off scheme that allows the MNOs to reduce their expenditures. The proposed scheme has been evaluated in terms of energy efficiency and cost metrics for various conditions (different bidding levels and behaviors). The results have shown that our proposal can significantly improve the network energy efficiency, guaranteeing at the same time the throughput. Regarding the financial costs/gains, the proposed scheme provides higher cost benefits and fairness compared with the state-of-the-art algorithms. It provides also interesting insights concerning the rules and behaviors that the MNOs should follow when they participate in an auction strategy. The study of other schemes for the solution of the problem (such as backwards induction) and the potential trade-offs would be interesting research line for future works.

References

[1] "Cisco visual networking index: Global mobile data traffic forecast update," Cisco, San Francisco, CA, USA, pp. 2014–2019, Feb. 2015.

[2] X. Bao, Y. Lin, U. Lee, I. Rimac, and R. R. Choudhury, "Dataspotting: Exploiting naturally clustered mobile devices to offload cellular traffic," in *Proc. IEEE INFOCOM*, Apr. 2013, pp. 420–424.

[3] "Nokia networks: Solutions," Nokia, Espoo, Finland, 2015. [Online]. Available: http://networks.nokia.com/portfolio/solutions/heterogeneous-networks

[4] L. Gao, G. Iosifidis, H. Jianwei, and L. Tassiulas, "Economics of mobile data offloading," in *Proc. IEEE Workshop INFOCOM*, Apr. 2013, pp. 3303–3308.

[5] W. Dong *et al.* "iDEAL: Incentivized dynamic cellular offloading via auctions," in *Proc. IEEE INFOCOM*, Apr. 2013, pp. 755–763.

[6] S. Paris, F. Martignon, I. Filippini, and A. Capone, "A truthful auction for access point selection in heterogeneous mobile networks," in *Proc. IEEE ICC*, Jun. 2012, pp. 3200–3205.

[7] X. Zhuo, W. Gao, G. Cao, and S. Hua, "An incentive framework for cellular traffic offloading," *IEEE Trans. Mobile Comput.*, vol. 13, no. 3, pp. 541–555, Mar. 2014.

[8] G. Fettweis and E. Zimmermann, "ICT energy consumption—trends and challenges," in *Proc. WPMC*, Sep. 2008, pp. 1–4.

[9] G. Auer *et al.*, "How much energy is needed to run a wireless network?" *IEEE Wireless Commun.*, vol. 18, no. 5, pp. 40–49, Oct. 2011.

[10] F. Han, Z. Safar, and K. J. R. Liu, "Energy-efficient base-station cooperative operation with guaranteed QoS," *IEEE Trans. Commun.*, vol. 61, no. 8, pp. 3505–3517, Aug. 2013.

[11] E. Oh, K. Son, and B. Krishnamachari, "Dynamic base station switching-on/off strategies for green cellular networks," *IEEE Trans. Wireless Commun.*, vol. 12, no. 5, pp. 2126–2136, May 2013.

[12] A. Bousia, E. Kartsakli, L. Alonso, and C. Verikoukis, "Dynamic energy efficient distance-aware base station switch on/off scheme for LTE-Advanced," in *Proc. IEEE GLOBECOM*, Dec. 2012, pp. 1532–1537.

[13] A. Bousia, E. Kartsakli, A. Antonopoulos, L. Alonso, and C. Verikoukis, "Game theoretic infrastructure sharing in multi-operator cellular networks," *IEEE Trans. Veh. Technol.*, DOI: 10.1109/TVT.2015.2445837, to be published.

[14] J. Bartelt, A. Fehske, H. Klessig, G. Fettweis, and J. Voigt, "Joint bandwidth allocation and small cell switching in heterogeneous networks," in *Proc. IEEE VTC—Fall*, Sep. 2013, pp. 1–5.

[15] Y. S. Soh, T. Q. S. Quek, M. Kountouris, and H. Shin, "Energy efficient heterogeneous cellular networks," *IEEE J. Sel. Areas Commun.*, vol. 31, no. 5, pp. 840–850, May 2013.

[16] M. H. Alsharif, R. Nordin, and M. Ismail, "A review on intelligent base stations cooperation management techniques for greener LTE cellular networks," *J. Commun.*, vol. 9, no. 12, pp. 937–945, Dec. 2014.

[17] S. Paris, F. Martignon, I. Filippini, and L. Chen, "A bandwidth trading marketplace for mobile data offloading," in *Proc. IEEE INFOCOM*, Apr. 2013, pp. 430–434.

[18] M. A. Marsan and M. Meo, "Network sharing and its energy benefits: A study of European mobile network operators," in *Proc. IEEE GLOBECOM*, Dec. 2013, pp. 2561–2567.

[19] "Small cell market status," Small Cell Forum, U.K., Feb. 2013. [Online]. Available: http://www.smallcellforum.org/resources-reports

[20] "3rd generation partnership project; technical specification group services and system aspects; telecommunication management; study on Energy Savings Management (ESM) (Release 10)," Third-Generation Partnership Project, Sophia Antipolis Cedex, France, Tech. Rep., 3GPP TR 32.826, V10.0.0, Mar. 2010.

[21] "Mobile traffic forecasts 2010–2020 Report," UMTS Forum, London, U.K., Jan. 2011.

[22] V. Krishna, *Auction Theory*. San Diego, CA, USA: Academic, 2010.

[23] A. Bousia, E. Kartsakli, A. Antonopoulos, L. Alonso, and C. Verikoukis, "Sharing the small cells for energy efficient networking: How much does it cost?" in *Proc. IEEE GLOBECOM*, Dec. 2014, pp. 2649–2654.

[24] Y. Sawaragi, I. Hirotaka, and T. Tanino, *Theory of Multiobjective Optimization*, 1st ed. New York, NY, USA: Academic, 1985.

[25] T. Weise, *Global Optimization Algorithms—Theory and Application*, 2nd ed. Hefei, China: Thomas Weise, 2009. [Online]. Available: http://www.it-weise.de/

[26] R. L. Carraway, T. L. Morin, and H. Moskowitz, "Generalized dynamic programming for multicriteria optimization," *Eur. J. Oper. Res.*, vol. 44, no. 1, pp. 95–104, Jan. 1990.

[27] H. G. Beyer and K. Deb, "On self-adaptive features in real-parameter evolutionary algorithms," *IEEE Trans. Evol. Comput.*, vol. 5, no. 3, pp. 250–270, Jun. 2001.

[28] C. A. Coello, G. B. Lamont, and D. A. Van Veldhuizen, *Evolutionary Algorithms for Solving Multi-Objective Problems*, ser. Genetic and Evolutionary Computation, 2nd ed. Berlin, Germany: Springer-Verlag, 2007.

[29] L. M. Schmitt, "Theory of genetic algorithms II: Models for genetic operators over the string-tensor representation of populations and convergence to global optima for arbitrary fitness function under scaling," *Theoretical Comput. Sci.*, vol. 310, pp. 181–231, 2004.

[30] "Ericsson mobility report: On the pulse of the networked society," Ericsson, Stockholm, Sweden, Tech. Rep. Nov. 2014.

[31] "Sitefinder: Mobile Phone Base Station Database," Ofcom, London, U.K., Mar. 2015. [Online]. Available: http://sitefinder.ofcom.org.uk/search

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Multiobjective Auction-Based Switching-Off Scheme in Heterogeneous Networks: To Bid or Not to Bid?

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***Abstract*—The emerging data traffic demand has caused a massive deployment of network infrastructure, including macro base stations (BSs) and small cells (SCs), leading to increased energy consumption and expenditures. However, the network underutilization during low traffic periods (e.g., night zone) enables the mobile network operators (MNOs) to save energy by having their traffic served by third-party SCs, thus being able to switch off their BSs. In this paper, we propose a novel market approach to foster the opportunistic utilization of the unexploited SCs capacity, where the MNOs, instead of requesting the maximum capacity to meet their highest traffic expectations, offer a set of bids requesting different amounts of resources from the third-party SCs at lower costs. Motivated by the conflicting financial interests of the MNOs and the third party, the restricted capacity of the SCs that is not adequate to carry the whole traffic in multioperator scenarios, and the necessity for energy-efficient solutions, we introduce a combinatorial auction framework, which includes 1) a bidding strategy, 2) a resource-allocation scheme, and 3) a pricing rule. We propose a multiobjective framework as an energy- and cost-efficient solution for the resource-allocation problem, and we provide extensive analytical and experimental results to estimate the potential energy and cost savings that can be achieved. In addition, we investigate the conditions under which the MNOs and the third-party companies should take part in the proposed auction.**

***Index Terms*—Auction, energy efficiency, game theory, green networking, heterogeneous networks (HetNets), multiobjective optimization, offloading, switching off.**

I. Introduction

A. Motivation

The rapid expansion of mobile services, along with the emerging demand for multimedia applications, driven by the widespread use of laptops, tablets, and smart devices, has led to an impressive growth of data traffic during the last few years. Global mobile data traffic is expected to increase nearly tenfold, reaching 24.3 EB per month by 2019 [1]. Hence, mobile network operators (MNOs[1]) seek to extend their infrastructure by installing more base stations (BSs). In an effort to increase the capacity of their network and meet these pressing traffic demands, they also lease capacity and bandwidth resources from third parties, who deploy low-powered small-cell (SC) networks to provide enhanced services via traffic offloading from macro BSs to SCs during peak hours [2]. For instance, Nokia Networks [3] has recently built networks of interconnected SCs, enabling operators to extend the coverage and increase the capacity of existing macro networks. The involvement of various entities of corporate nature with different financial goals generates a new ecosystem with interesting dynamics to be studied. To that end, in [4], the economics of offloading are investigated, whereas auction theory is used to model economic transactions between conflicting parties in several works [5]–[7] through offloading schemes with auction-based resource-allocation problems.

The dense heterogeneous networks (HetNets) imply significant increase in the capital and operational expenditures (CapEx and OpEx) of MNOs [8], and as a result, there is a strong motivation to investigate energy-efficient solutions to bring down the energy consumption and the cost of networks. This goal can be accomplished through the switching off of the underutilized nodes when the traffic is significantly low. Since the BSs are the most power hungry and expensive components of the networks [9], the research community has shifted toward the investigation of BS switching-off schemes [10]–[15]. Despite their promising results, these works examine only one tier of macro BSs, whereas the presence of multiple MNOs raises new challenges and open issues.

The SC deployment in current HetNets can be the key to implementing novel energy and cost-efficient solutions. By encouraging the traffic offloading from BSs to SCs during low traffic periods, when the SC resources are most likely to remain unused, part of the BS infrastructure can be switched off. Given that the energy consumption of the BSs is considerably higher with respect to the SCs, even when the traffic load is low, such solutions can yield high energy gains for the MNOs. Thus, offloading can be exploited to concentrate the users to the SCs

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[1]The terms "MNO" and "operator" will be used interchangeably in the remainder of this paper.

and allow the BSs with no traffic to be switched off. However, despite the potential gains of the opportunistic exploitation of the capacity of SCs and the deactivation of the redundant BSs during low traffic conditions, very few research works exist in the literature so far.

An overview of the existing techniques in energy-efficient network planning is presented in [16], highlighting the advantages and the shortcomings of the algorithms and revealing the open issues that should be further studied in the field of HetNets and operators' collaboration. In the same context, in [17], an auction-based offloading scheme is proposed for the BS switching off, where the operators submit a bidding value, and a third party's income optimization approach is followed to solve the resource-allocation problem. However, only a particular network configuration is considered, where it is assumed that the SC capacity is sufficient to serve the traffic of the network, allowing the switching off of all the BSs.

Despite the clear benefits of the BSs switching off via offloading, the presence of multiple MNOs in the same area [18] would complicate the application of this scheme since the SCs may not be able to fully support the network traffic. Another limitation of the auction-based state-of-the-art works [5], [6], [17] consists in the fact that the MNOs propose a single bidding value for the requested capacity, based on the maximum predictions about the traffic that they are willing to offload. However, these predictions do not always correspond to the real traffic values, which can be significantly lower than the maximum values, leading to increased costs for the operators and inefficient use of the SC capacity resources.

B. Contribution

In this paper, motivated by the aforementioned issues, we propose a novel energy-efficient solution for dense HetNets, which considers the interests of the involved parties (MNOs and third party) and the time-varying traffic characteristics. More specifically, we introduce an offloading mechanism, where the operators lease the capacity of an SC network owned by a third party, to be able to switch off their BSs and maximize their energy efficiency, when the traffic demand is low. The MNOs request capacity from several SCs and can only switch off their BSs if all their requests are satisfied, enabling them to offload all their traffic to the SC network.

To that end, the allocation of the SC resources among a set of competing MNOs is mathematically formulated as an auction. Since the exact resource requirements of the network are unknown beforehand, the MNOs employ past reports to predict the maximum expected traffic load. Then, exploiting the fact that, with a high probability, the actual traffic will be lower than the predicted maximum (especially during low traffic periods), the MNOs submit a set of bids to the SCs, requesting for lower capacity resources (with respect to the maximum estimated requirements). With this approach, the SC resources can be more efficiently utilized, and the MNOs are likely to pay a lower price for the leased capacity, taking a small risk of not being able to serve all users under some circumstances (i.e., when the traffic approaches the maximum predictions and the leased capacity is not sufficient). Our key contribution is to study this very interesting trade-off between the potential energy and financial gains of this solution and the risk of not fully satisfying all the users, thus providing the MNOs with the necessary insights to decide whether it is profitable to participate in the auction, depending on their tolerance to the potential loss of some users.

In addition, the conflicting interests of the involved parties are also taken into consideration. On the one hand, the MNOs aim to reduce their energy consumption and expenditures by offloading their traffic and switching off their BS infrastructure. However, to deactivate a BS, all its traffic should be offloaded to the SC network (i.e., the MNO should win in all the auctions involving the particular BS). On the other hand, the third party wants to maximize its income by leasing the maximum possible amount for resources to the MNOs. However, the resource allocation policy that maximizes the third party's income may not enable the operators to switch off their BSs. Our proposed auction-based strategy takes into account these conflicting interests to achieve a feasible, efficient, and energy-saving resource-allocation scheme.

In summary, the contribution of this paper is described as follows.

1) *Bidding Strategy*: We propose a novel bidding strategy, where MNOs submit a set of bids (and not only one bid) to the third party, requesting different capacity resources, based on the predictions about their maximum traffic. The diversity of bids allows more offloading opportunities, which is profitable for both the MNOs and the third party.
2) *Auction Design and Switching Off Decision*: We design an auction scheme that enables the efficient usage of SCs resources under low traffic conditions. Our framework motivates the MNOs to quantify their tolerance about requesting fewer resources and form the different levels of bids. We show that the proposed auction-based scheme has two desirable properties: 1) truthfulness; and 2) individual rationality. The mechanism is designed based on a multiobjective framework, where the conflicting interests of the involved parties are considered, to provide the optimal solution that maximizes the economic profit of both the third party and the MNOs and minimizes the network energy consumption at the same time.
3) *Performance Evaluation*: We validate the theoretical analysis of the multiobjective problem by computing the Pareto front (i.e., the set of optimal) solutions and assess the effectiveness of the proposed auction-based switching-off algorithm. The analytical and simulation results indicate the potential energy efficiency and economic gains in the network and give the necessary insights to the MNOs to decide whether it is beneficial to enter in a resource allocation negotiation with the third party.

The remainder of this paper is organized as follows. The system model is described in Section II. In Section III, we introduce the auction-based optimization approach that is used for the BSs' switching-off decision. The performance evaluation is provided in Sections IV and V concludes this paper.

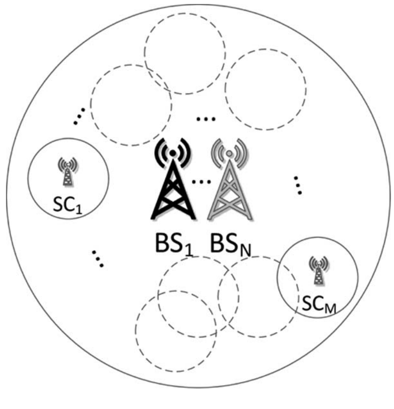

Fig. 1. Network configuration with one macro cell served by N MNOs and covered by M third-party SCs.

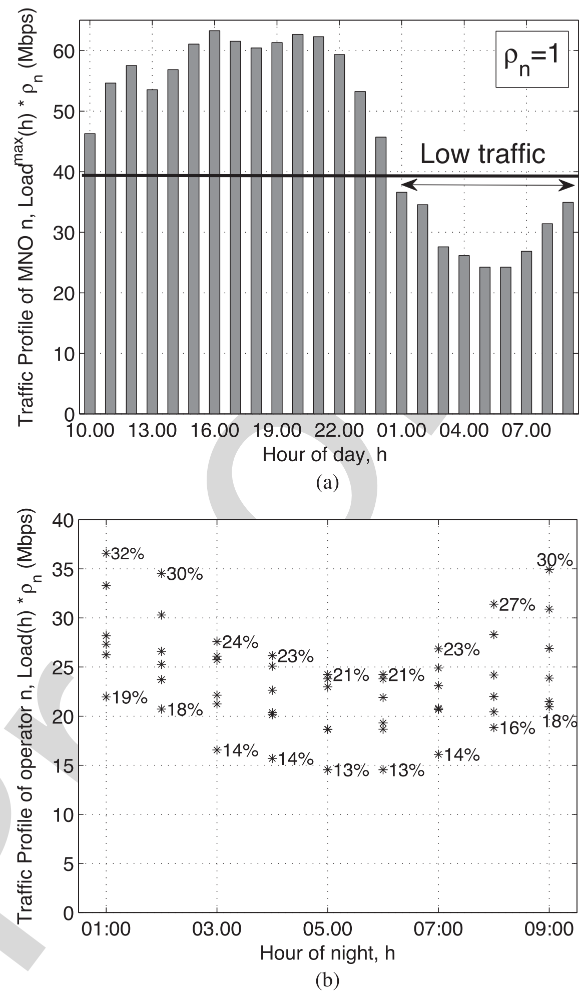

Fig. 2. Traffic pattern scenario and real data traffic values. (a) Traffic load during the 24-hour day. (b) Real data for traffic load patterns.

II. System Model and Operation

A. Network Configuration

We consider an urban scenario, focusing on an area of a macro cell. In the macro cell, we assume that N MNOs provide coverage through their BSs, which are denoted by BS_n, where $n \in \mathcal{N} = \{1, \ldots, N\}$ characterizes the MNO_n. Let us highlight that, in dense networks, due to legal regulations, MNOs are obligated to install their antennas and BSs on the same buildings; thus, we examine networks with collocated BSs [18]. Moreover, in the macro cell, SCs, owned by a third party, are randomly distributed. Each SC is represented as SC_m, where $m \in \mathcal{M} = \{1, \ldots, M\}$. We assume that the number of SCs is adequate to cover the area of the macro cell [19]. As it will be explained in the following, the MNOs are motivated to offload their traffic to the third-party SCs by paying the corresponding price, thus enabling part of BS infrastructure to be switched off during low traffic conditions. The network configuration is shown in Fig. 1.

B. Traffic Load Model

In this paper, we adopt a realistic traffic pattern [20], [21] that corresponds to the maximum traffic per operator in a given cell. Fig. 2(a) plots the maximum traffic per hour, which is denoted by $\mathrm{Load}^{\max}(h)$, throughout the day.[2] Without loss of generality, we focus on the time zone between 01:00 A.M. and 09:00 A.M., when the traffic per BS is relatively low (i.e., less than 40 Mb/s, which corresponds to 35% of the cell's capacity). The selection of the night zone may vary according to the traffic variations, and our algorithm can be adapted to different traffic conditions. In addition, we assume that the traffic volumes of different MNOs may be different, although they follow the same pattern. Hence, we define $\rho_n \in [0, 1]$ as the percentage of each operator's traffic load with respect to the maximum traffic for the respective hour. In this paper, we have used traffic data sets that include information of one operator for ten BSs during the period of one year, thus including weekends, weekdays, and day and night hours. To that end, the reports consists of various values for both low and high traffic. Provided that the data sets had huge information, we classified the days of the year into different periods of time (e.g., seasons, weekdays, and weekends). Based on these real traffic reports and by using simple statistical analysis, we have obtained the necessary insights about the minimum, maximum, and average values of the traffic load, and we have plotted some indicative numbers in Fig. 2(b). Each one of the six values corresponds to the average traffic that was observed in different days during the year. In addition, we express the BS utilization as a percentage of the total BS's capacity resources for the extreme cases of minimum and maximum traffic loads. The two values, i.e., $\mathrm{Load}^{\min}$ and $\mathrm{Load}^{\max}$, are very critical, and it is very important for the MNOs to be able to predict them.

Unlike the existing works in the literature, where each MNO places only one bid corresponding to the maximum capacity requirements, in this paper, we propose that the MNOs place multiple bids corresponding to different levels of the predicted traffic load, as shown in Fig. 2(b). Thus, given the estimated minimum and maximum traffic load levels and assuming that the actual traffic values will, most probably, lie between these extreme values, we are able to calculate different levels of traffic. In this paper, we consider $L + 1$ different traffic load levels. The number of levels depends on the MNOs' strategy

[2]The parameter h can be dropped for the sake of simplicity.

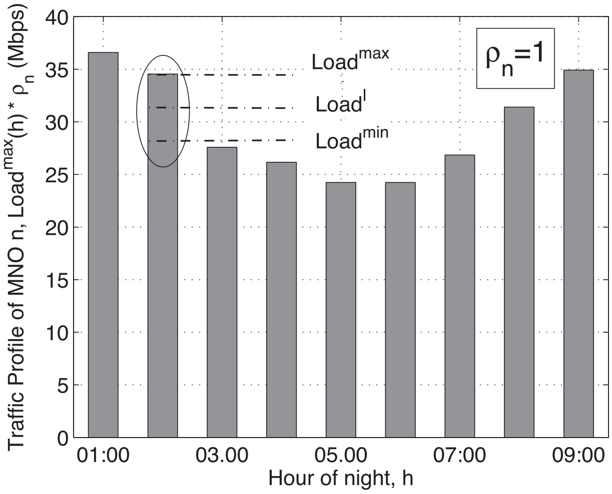

Fig. 3. Traffic during the night zone and different levels of traffic estimation.

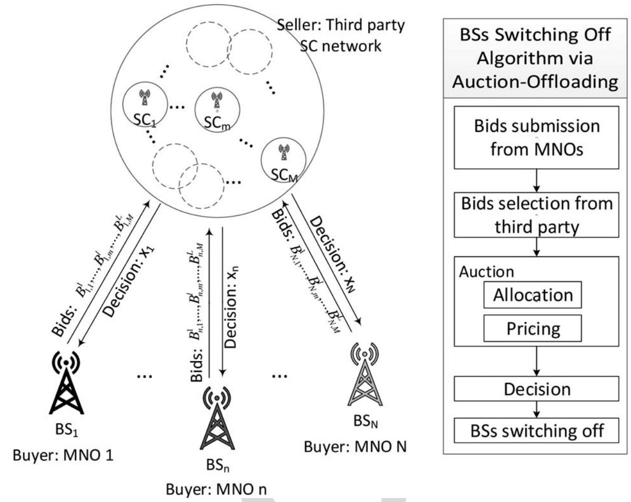

Fig. 4. Auction illustration and proposed algorithm flowchart.

that will be further explained in the following. Each level $l \in \mathcal{L} = \{0, \ldots, L\}$ corresponds to traffic that is equal to

$$\begin{aligned}\mathrm{Load}^l &= \mathrm{Load}^{\min} + \frac{\mathrm{Load}^{\max} - \mathrm{Load}^{\min}}{L} \cdot l \\ &= \left(1 - \frac{l}{L}\right) \cdot \mathrm{Load}^{\min} + \frac{l}{L} \cdot \mathrm{Load}^{\max}. \end{aligned} \tag{1}$$

Evidently, the two extreme values are $\mathrm{Load}^0 = \mathrm{Load}^{\min}$ and $\mathrm{Load}^L = \mathrm{Load}^{\max}$. Fig. 3 shows an example, depicting various traffic levels for a specific hour ($\mathrm{h} = 02{:}00$ A.M.). Based on the above, Appendix A of the supplemental file provides a theoretical estimation of the traffic that can be offloaded, explaining the process of mapping the users of the MNOs to the capacity of the SCs.

III. Auction-Based Switching-Off Algorithm

Here, we present the combinatorial auction employed to select the MNOs that can offload their traffic to the SCs, thus being able to switch off their BSs. We provide the bidding strategy, and we formulate the integer linear programming model, which ensures the optimal allocation and the switching-off strategy for the auction. In addition, to ensure truthful bidding, the Vickrey—Clarke—Grooves (VCG) payment mechanism [22] is employed.

A. Big Picture

By considering the limited capacity of the SCs and the MNOs' incentive to switch off their BSs, we use an auction-based mechanism to motivate the operators to offload the traffic to the third-party SC network. Fig. 4 illustrates the main idea of the scheme. In our proposal, both the MNOs and the third party take part in the decision process, each one having a separate role in the framework. On one hand, the MNOs act as buyers, who are willing to lease the SCs resources and opportunistically offload their traffic. On the other hand, the third party, acting as a seller, collects the bids, and through an auction, the subset of MNOs that can offload their traffic, is selected. The proposed auction-based switching-off scheme consists of three main steps: bidding, allocation, and pricing, whose process and the respective decision-makers (in parenthesis) are presented as follows. First, in the *bidding phase* (MNOs), the MNOs place their bids to the third party according to the different values of the requested bandwidth. Each bid includes the information of the requested capacity and the corresponding price that the MNO is willing to offer. Second, in the *allocation step* (third party and MNOs), the third party collects the MNOs' bids. The selection of the optimal resource allocation can be derived through the solution of the resource-allocation problem. Third, in the *pricing step* (third party), the third party decides each winner's payment price, based on the resource allocation of the previous step. The winning MNOs offload their whole traffic to the SCs and switch off their BSs, whereas the losing bidders keep their BSs active.

B. Bidding Strategy

Each SC_m of the third party (seller) has unexploited capacity resources that is willing to lease to the MNOs. The MNOs (buyers) want to offload their traffic to the SCs by requesting specific capacity resources to lease, based on the predictions of the traffic load. The number of the physical resource blocks (PRBs) is calculated in Appendix A of the supplementary AQ1 file. The MNOs valuate the requested resource $N^l_{\mathrm{PRB}_{n,m}}$ at a given price $u^l_{n,m}$, unknown to the third party and the other bidders, where l is the level of resources, $n \in \mathcal{N}$ refers to the corresponding operator, and $m \in \mathcal{M}$ corresponds to the specific SC that the MNO wants to lease the resources from. In the proposed auction-based scheme, each operator submits a set of bid pairs $B^l_{n,m} = (b^l_{n,m}, N^l_{\mathrm{PRB}_{n,m}})$, representing the price $b^l_{n,m} \le u^l_{n,m}$, which the nth MNO pays for leasing the capacity $N^l_{\mathrm{PRB}_{n,m}}$ from the mth SC. In general, these two values (i.e., $b^l_{n,m}, u^l_{n,m}$) may not necessarily be the same. However, in a truthful auction such as the one that we have (the truthfulness property of the auction will be explained in Section III-D), it is proved that the private valuation and the bidding price are equal; thus, $b^l_{n,m} = u^l_{n,m}$ [5], [6]. After the reception bid pairs, the selection of the subset of the MNOs, whose traffic can be offloaded to the corresponding SCs, follows.

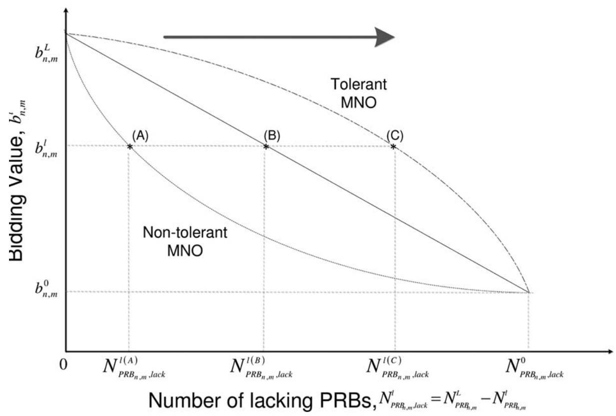

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Fig. 5. Bidding strategy versus tolerance function.

To gain further insights on the bidding strategy, let us consider the following example. Given the predicted expectations about the traffic, each MNO m submits multiple bids, $b^0_{n,m}, b^1_{n,m}, \ldots, b^l_{n,m}, \ldots, b^L_{n,m}$, indicating the offered price for the requested number of PRBs. Through the different bid pairs, the MNOs actually reveal their outage probability tolerance. In particular, by leasing the maximum calculated number of PRBs ($N^L_{\mathrm{PRB}_{n,m}}$) for the highest bid $b^L_{n,m}$, the MNOs guarantee service to all their users. Controversially, by obtaining a smaller number of PRBs (e.g., $N^l_{\mathrm{PRB}_{n,m}}$ with $l < L$), the MNO pays a smaller price at a risk of leaving some users in outage. The minimum number of requested PRBs $N^0_{\mathrm{PRB}_{n,m}}$ constitutes an upper bound of the operator's outage tolerance. Another parameter determined by each MNO is the number of levels. A higher number of levels results in more bid pairs, thus increasing the performance of the auction while inducing more communication overhead and higher computational complexity.

To flexibly model the MNOs' outage tolerance, we introduce a satisfaction function that represents the bidding value (which is equal to the valuation price) that the MNO is willing to pay for leasing a specific bandwidth. To that end, we define the number of lacking PRBs as the difference between the maximum number of PRBs minus the actually obtained PRBs allocated the MNO, given by

$$N^l_{\mathrm{PRB}_{n,m},\mathrm{lack}} = N^L_{\mathrm{PRB}_{n,m}} - N^l_{\mathrm{PRB}_{n,m}}. \quad (2)$$

The satisfaction function is determined by the requested capacity of each MNO and is monotonically decreasing with the number of lacking PRBs. We also consider that, for each MNO, there is a lower bound for the minimum number of requested PRBs, which minimizes the MNO's satisfaction. This bound indicates that for fewer PRBs the MNO will not participate in the auction. Fig. 5 shows three examples of the outage tolerance function. Three bidding values are emphasized in the plot: The highest bid $b^L_{n,m}$, corresponding to the maximum requested capacity $N^L_{\mathrm{PRB}_{n,m}}$ (with $N^l_{\mathrm{PRB}_{n,m},\mathrm{lack}} = 0$), the lowest bid $b^0_{n,m}$, and an intermediate value $b^l_{n,m}$. As the number of lacking PRBs increases (depicted by the arrow direction in Fig. 5), the bid values decrease, and as a consequence, losses in terms of the served users may be observed. If the number of lacking PRBs exceeds $N^0_{\mathrm{PRB}_{n,m},\mathrm{lack}}$, the MNO will not participate in the auction; thus, no bid lower than $b^0_{n,m}$ will be submitted. The three points (A, B, and C) marked in Fig. 5 correspond to the different tolerance functions of three operators. An outage-tolerant MNO (point C) requests for less bandwidth for the same bidding value $b^l_{n,m}$ compared with a nontolerant MNO (point A) that still requests high capacity from the third party. Hence, the nontolerant MNO places higher priority on guaranteeing user service, whereas the outage-tolerant MNO is willing to sacrifice some resources to increase its probability of winning the auction and switching off its BS, thus enhancing energy efficiency. Finally, point B corresponds to an intermediate bidding strategy defined by a linear function between the two examined parameters.

The user outage tolerance function (keeping in mind that $b^l_{n,m} = u^l_{n,m}$) is modeled as[3]

$$b^l_{n,m} = b^L_{n,m} - \frac{b^L_{n,m} - b^0_{n,m}}{N^L_{\mathrm{PRB}_{n,m}} - N^0_{\mathrm{PRB}_{n,m}}} \cdot \left(N^l_{\mathrm{PRB}_{n,m}}\right)^{\delta}. \quad (3)$$

The distinctive cases for the satisfaction curves are as follows.

- *Nontolerant MNO (Point A)*: For the nontolerant MNO, the outage tolerance function is convex, with $\delta < 1$.
- *Average-tolerant MNO (Point B)*. There is a linear relation between the bidding strategies and the outage tolerance of the MNOs, by substituting $\delta = 1$ in (3).
- *Tolerant MNO (Point C)*. For the tolerant MNO, the satisfaction function is concave, with $\delta > 1$.

The parameter δ may obtain a wide range of values. The selection of a value equal to $\delta \ll 1$ corresponds to a strictly nontolerant MNO, who decreases its bid requests very fast. In contrast, a very high value of this indicative parameter (i.e., $\delta \gg 1$) would lead to very slowly decreasing bidding values and, thus, to a very tolerant operator.

C. Auction Formulation

By employing the properties of combinatorial auction theory, we formulate the problem of the opportunistic offloading as an auction. Each MNO $n \in \mathcal{N}$ places the corresponding bid pairs $B^l_{n,m}$. Having received the bids, the third party selects the subset of MNOs that maximizes the desired goals of all the involved participants. We define $x^l_{n,m}$ as a binary decision variable that indicates whether the corresponding bidder (MNO n) is winner ($x^l_{n,m} = 1$) or not ($x^l_{n,m} = 0$) in the corresponding SC_m and for the lth bidding value.

The cost of using the SC infrastructure and the increased consumed energy are the main objectives: the maximization of the profits (the economic objectives of the third party and the MNOs) and the minimization of the energy consumption (the energy objective). In continuation, a detailed analysis of the objectives of each party is presented.

1) Third Party's Objective: The third party aims at *maximizing its profit* by leasing high volumes of the capacity of SCs at

[3]The values of $b^0_{n,m}$ and $b^L_{n,m}$ will be calculated in details in the succeeding section, where the constraints and requirements posed by the MNOs and the third party are given within the optimization framework.

increased prices. The profit is defined as the difference of the MNOs' winning bids minus its expenses (CapEx and OpEx). We define the financial gain of the SC network $\mathrm{CG}_{\mathrm{SC}}$ as

$$f_1(\mathbf{x}) = \mathrm{CG}_{\mathrm{SC}} = \sum_{n\in\mathcal{N}} \sum_{m\in\mathcal{M}} \sum_{l\in\mathcal{L}} x^l_{n,m} \cdot b^l_{n,m} - M \cdot C_{\mathrm{SC}} \quad (4)$$

where C_{SC} is the cost of a SC, corresponding to the sum of its CapEx and the traffic-dependent OpEx. For the calculation of the SCs cost, the cost model presented in [23] is employed.

To ensure its objective, the third party introduces a minimum profit, which is described as a function of its total cost, i.e.,

$$\mathrm{CG}^{\min}_{\mathrm{SC}} = y \cdot M \cdot C_{\mathrm{SC}}, \quad y > 0. \quad (5)$$

Given the minimum profit, which is calculated by (5), we estimate the reservation price as follows.

Proposition 1: The reservation price is defined as the minimum price that a seller would be willing to accept for leasing the corresponding bandwidth, i.e.,

$$b^l_{\mathrm{res},n,m} = \frac{N^l_{\mathrm{PRB}_{n,m}}}{N^{\max}_{\mathrm{PRB}}} \cdot y \cdot M \cdot C_{\mathrm{SC}}. \quad (6)$$

Proof: The third party is willing to share its resources among the MNOs based on proportional fairness by ensuring that a minimum profit gain will be achieved, at the same time. To that end, it calculates a reservation price, which is the minimum price that the third party will accept from an MNO to lease a specific bandwidth. The maximum number of PRBs that the nth MNO can offload to the mth SC is given by

$$N^l_{\mathrm{PRB}_{n,m}} = \frac{b^l_{\mathrm{res},n,m} \cdot x^l_{n,m}}{\sum\limits_{n\in\mathcal{N}} \sum\limits_{l\in\mathcal{L}} b^l_{\mathrm{res},n,m} \cdot x^l_{n,m}} \cdot N^{\max}_{\mathrm{PRB}}. \quad (7)$$

Finally, by using (5) and (7) in (4), the reservation price for offloading traffic is calculated. ∎

The reservation price in (6) is not the price that the MNOs will propose to lease their requested capacity, although it is a threshold price that the third party uses to eliminate all the offers that are less than the accepted. The reservation price can be either announced or unknown to the MNOs. The reservation price means that the seller would rather withhold the capacity if the proposed bids are too low (i.e., lower than the reservation price), and given this price, the auction process can be accelerated since the set of prices that are lower than the reservation price can be discarded.

2) MNOs' Objective: The objective of each MNO is the *maximization of its financial profits*. The maximization of the profits of the nth MNO is defined as the revenue from switching off its BS minus the winning bids for leasing the requested capacity from the third party. Therefore, the profit (cost gain) can be written as

$$f_2(\mathbf{x}) = \mathrm{CG}_n = C_{\mathrm{BS}} \cdot x_n - \sum_{m\in\mathcal{M}} \sum_{l\in\mathcal{L}} x^l_{n,m} \cdot b^l_{n,m} \quad (8)$$

with

$$x_n = \prod_{m\in\mathcal{M}} \sum_{l\in\mathcal{L}} x^l_{n,m} \quad \forall\, n \in \mathcal{N} \quad (9)$$

and C_{BS} being the cost of a BS, whose model is also presented in [23], provided that

$$\sum_{l\in\mathcal{L}} x^l_{n,m} \in \{0,1\} \quad \forall\, n \in \mathcal{N} \quad \forall\, l \in \mathcal{L}. \quad (10)$$

At this point, let us recall that an operator is able to switch off its BS if it wins in an auction in all the SCs, a condition that is represented by the product in (9). The product is equal to 1 only when the nth MNO wins in M auctions in respective SCs; otherwise, it is 0.

The MNOs are willing to participate in the auction and lease bandwidth resources from a third party if they guarantee a minimum profit gain. Consequently, they introduce a minimum profit, which is described as a percentage of their total costs, i.e.,

$$\mathrm{CG}^{\min}_n = z \cdot C_{\mathrm{BS}}, \quad 0 < z < 1. \quad (11)$$

The bidding strategy of the MNOs, along with the proposed bids, depend on the minimum profit gain and the operation costs of the BSs. However, the cost gain can be attained if and only if the nth MNO wins in M auctions and is able to lease the requested capacity. In addition, since we consider uniform traffic in the macro cell, we conclude that the bids in the different SCs must be equal and proportional to the corresponding traffic. Thus, the maximum bid price for offloading the traffic in the mth cell is calculated as

$$b^L_{n,m} = \frac{(1-z) \cdot C_{\mathrm{BS}}}{M}. \quad (12)$$

Similarly, the minimum bidding price is a proportional value of the maximum one, which is given by

$$b^0_{n,m} = v \cdot \frac{(1-z) \cdot C_{\mathrm{BS}}}{M} \quad (13)$$

where $v \in (0,1)$. The bidding values of the remaining $L-1$ levels can be calculated based on (3), depending on the maximum bid value and the relation between the outage tolerance of the MNOs and the discount they can be offered for the lower requested bandwidth.

3) Overall Objective: The overall objective of the network is the *minimization of the energy consumption*. This can be attained by reducing the number of active BSs, given that the BSs are responsible for the major part of energy consumption in the network. The network energy consumption $\mathbb{E}[E]$ is

$$f_3(\mathbf{x}) = \mathbb{E}[E] = \sum_{n\in\mathcal{N}} \mathbb{E}\left[E_{\mathrm{BS}_n}\right] \cdot (1 - x_n) + M \cdot \mathbb{E}[E_{\mathrm{SC}}] \quad (14)$$

where $\mathbb{E}[E_{\mathrm{BS}_n}]$ and $\mathbb{E}[E_{\mathrm{SC}}]$ represent the energy consumption of BS and SC, respectively.

The combinatorial auction formulation should include all the objectives of the participating entities. To capture the trade-off between the objectives, the multiobjective optimization [24] is employed. The target is to find a subset of acceptable solutions according to a set of objectives. In general terms, the objectives may be conflicting, and consequently, a single global optimum may not exist. Hence, the notion of an optimum set $\mathbf{x}^*$ becomes very important. Some relevant definitions are given in the following.

Definition 1: Given the three objectives, $f_1(\mathbf{x})$, $f_2(\mathbf{x})$, and $f_3(\mathbf{x})$, and provided that $\mathbf{x}_1$ and $\mathbf{x}_2$ are two decision variables, then $\mathbf{x}_1$ is said to be the Pareto dominant, and is denoted $\mathbf{x}_1 \succeq \mathbf{x}_2$ if and only if $f_i(\mathbf{x}_1) \geq f_i(\mathbf{x}_2)\ \forall i \in \{1,2,3\}$, and $f_j(\mathbf{x}_1) > f_j(\mathbf{x}_2)$, for at least one index $j \in \{1,2,3\}$.

Definition 2: $\mathbf{x}^*$ is said to be Pareto optimal (or nondominated), if there is no other $\mathbf{x}$, so that $\mathbf{x}$ dominates $\mathbf{x}^*$. The set of all Pareto solutions in the decision space is called the Pareto optimal set and the image of the Pareto optimal set in the objective space is called the Pareto optimal front.

AQ3 Based on the aforementioned definitions, the ILP multiobjective optimization problem can be formulated as follows.

Definition 3: The allocation problem is to determine the optimal solution $\{x^l_{n,m}\}\ \forall n \in \mathcal{N}\ \forall m \in \mathcal{M}$, and $\forall l \in \mathcal{L}$ that maximizes the distinctive objectives of the involved parties in the auction, subject to capacity and offloading targets

$$\mathbf{P1}:\ \max\ [\mathrm{CG}_{\mathrm{SC}},\ \mathrm{CG}_n,\ -\mathbb{E}[E]] \tag{15}$$

s.t.

$$\sum_{n\in\mathcal{N}}\sum_{l\in\mathcal{L}} x^l_{n,m}\cdot N^l_{\mathrm{PRB}_{n,m}} \leq N^{\max}_{\mathrm{PRB}}\quad \forall m \in \mathcal{M} \tag{16}$$

$$\sum_{l\in\mathcal{L}} x^l_{n,m} \in \{0,1\}\quad \forall n\in\mathcal{N}\quad \forall m \in \mathcal{M} \tag{17}$$

$$b^l_{n,m} \geq b^l_{\mathrm{res},n,m}\quad \forall n\in\mathcal{N}\quad \forall m\in\mathcal{M}\quad \forall l\in\mathcal{L} \tag{18}$$

$$x^l_{n,m} \in \{0,1\}\quad \forall n\in\mathcal{N}\quad \forall m\in\mathcal{M}\quad \forall l\in\mathcal{L}. \tag{19}$$

The constraint in (16) ensures that the total number of allocated resources does not exceed their availability, constraint (17) ensures that only one bid of the nth MNO in the mth SC can be the winning bid among the l different ones, constraint (18) ensures that the bids are higher than the reservation price, and constraint (19) ensures the integrality of the binary variable. The objectives of the proposed optimization formulation are contradictory. The maximization of the third party income does not imply the BSs switching off, whereas the energy objective does not ensure the third party's interests. The maximization of the financial gains of the third party may lead to additional economic losses from the MNOs' perspective since the maximization of this objective may lead to a resource allocation that does not imply the deactivation of BSs.

Exploiting the fact that the BSs are responsible for the major part of the energy consumption, the third objective of the problem $f_3(\mathbf{x})$ can be transformed into a constraint. Energy consumption is minimized when the maximum number of MNOs switches off their BSs after winning in M auctions, a condition represented by the product in (9). Thus, the problem **P1** is transformed into a simpler formulation in (20), and at the same time, the energy consumption objective is not neglected, in contrast to former works [17], where only the maximization of the third party's income is considered. The equivalent problem is as follows:

$$\mathbf{P2}:\ \max\ [\mathrm{CG}_{\mathrm{SC}},\ \mathrm{CG}_n] \tag{20}$$

s.t.

$$\prod_{m\in\mathcal{M}}\sum_{l\in\mathcal{L}} x^l_{n,m} \in \{0,1\}\quad \forall n \in \mathcal{N} \tag{21}$$

$$\sum_{n\in\mathcal{N}}\sum_{l\in\mathcal{L}} x^l_{n,m}\cdot N^l_{\mathrm{PRB}_{n,m}} \leq N^{\max}_{\mathrm{PRB}}\quad \forall m \in \mathcal{M} \tag{22}$$

$$\sum_{l\in\mathcal{L}} x^l_{n,m} \in \{0,1\}\quad \forall n\in\mathcal{N}\quad \forall m \in \mathcal{M} \tag{23}$$

$$b^l_{n,m} \geq b^l_{\mathrm{res},n,m}\quad \forall n\in\mathcal{N}\quad \forall m\in\mathcal{M}\quad \forall l\in\mathcal{L} \tag{24}$$

$$x^l_{n,m} \in \{0,1\}\quad \forall n\in\mathcal{N}\quad \forall m\in\mathcal{M}\quad \forall l\in\mathcal{L}. \tag{25}$$

The objective function (20) aims at maximizing the financial gain of both the third party and the MNOs. Constraint (21) ensures that an operator either wins in one auction in the M SCs (and switches off its BS) or loses in all the auctions (keeps its BS active). Thus, this constraint ensures the minimization of the energy consumption given by (14) since the selected resource allocation leads to the highest number of switched-off BSs, while at the same time achieving the increase in MNOs and third party's income. Constraints (22)–(25) are the same as (16)–(19), respectively.

The multiobjective problem **P2** belongs to the class NP-Complete since it is equivalent to the 0–1 knapsack problem, which is a well-known problem in combinatorial optimization. For the NP-hard problems, an optimal solution is difficult to be found due to the large number of variables [24]. However, there are different solutions that represent the best feasible state of the investigated system, e.g., the best resource allocation for the deactivation of the highest number of BSs. To find the best possible representation or a good approximation of these optimal solutions that are widely known as the Pareto optimal set or as the optimal Pareto front and to overcome the high complexity of multiobjective problems, metaheuristic methods (also sometimes called genetics) have become a very active research area, and several algorithms have been proposed [25], [26]. Although, the metaheuristic algorithms do not guarantee that this approximation is the optimal, the solutions are still good and near optimal.[4]

The metaheuristic algorithm that finds the Pareto solution for our multiobjective optimization problem works on a set of possible combinations of the decision variables [24]. The basic definition of the Pareto front is that it consists of exactly those point solutions that are not dominated by any other point. The different objectives cannot be optimized simultaneously. Thus, first, the solutions that maximize the MNOs's income and the third party's economic gains are calculated separately.

[4]For the sake of simplicity, we use the term "Pareto front" throughout this paper to refer to the obtained solutions through metaheuristics.

Obviously, these solutions that maximize the cost gains of the MNOs and the third-party always belong to the Pareto front and, in fact, they are its endpoints. A simple algorithm to find the other solutions (if any) on the Pareto front begins by sorting the solutions according to one of the objectives, e.g., third party's income. The algorithm then starts with the point with the maximum gain for the third party and continues to the successive solutions in order of increasing third party's cost until the solutions with higher cost gain value for the operators is found. This solution is then added to the Pareto front, and the search is restarted from it.

Through the use of metaheuristics, the problem can be solved efficiently and quickly for a relatively small number of MNOs and SCs [25], [27], [28]. This assertion cannot be concluded and generalized for large networks. In the investigated network configuration with 5 MNOs, 15 SCs, and 9 bidding levels, the runtime of the solution is very short. At this point, let us clarify that the numbers selected for the MNOs and the SCs are based on the most typical and realistic scenarios in recent studies [18], [19] since the most common scenarios in European countries involve three to four MNOs, and 15 SCs can cover the service are of one macro BS.

D. Pricing Strategy

Having defined the ILP model, we now illustrate the payment rule, which is of crucial importance for the realization of the auction for the third party. The VCG payment induces all the users to reveal their actual valuations for the requested bandwidth. In the VCG mechanism, the third party charges the bidders (MNOs) with a price for the requested capacity. For example, an MNO who requires large bandwidth will have to pay a high price since its request results in dissatisfying other MNOs who lose in the auction because of the limited capacity resources and will not be able to offload their traffic.

Let us denote by $p^l_{n,m}$ the price paid by the MNO n to the third party for the allocated capacity of the mth SC. The payoff function for bidder n that represents the difference between the gain of the MNO attained through the BS switching off and the true valuation minus the paid price (let us recall that in the truthful auction $u^l_{n,m} = b^l_{n,m}$) is

$$\mathcal{U}_i = \begin{cases} \mathrm{CG}_i + \sum\limits_{m\in\mathcal{M}} \sum\limits_{l\in\mathcal{L}} u^l_{i,m} - \sum\limits_{m\in\mathcal{M}} \sum\limits_{l\in\mathcal{L}} p^l_{i,m}, & \text{if } i \text{ is selected} \\ -C_{\mathrm{BS}}, & \text{otherwise.} \end{cases} \tag{26}$$

The payment rule for each MNO can be defined as follows:

$$\begin{aligned} p^l_{i,m} = & \sum_{n\in\mathcal{N}\setminus\{i\}} \sum_{m\in\mathcal{M}} \sum_{l\in\mathcal{L}} \left(x^l_{i,m}\right)^{\{-i\}} \cdot b^l_{i,m} \\ & - \left(\sum_{n\in\mathcal{N}\setminus\{i\}} \sum_{m\in\mathcal{M}} \sum_{l\in\mathcal{L}} x^l_{i,m} \cdot b^l_{i,m} \right. \\ & \left. - \sum_{n\in\mathcal{N}\setminus\{i\}} \sum_{m\in\mathcal{M}} \sum_{l\in\mathcal{L}} x^l_{i,m} \cdot b^l_{i,m} \right) \end{aligned} \tag{27}$$

TABLE I
SIMULATION PARAMETERS

Parameter	Value	Parameter	Value
Number of MNOs, N	5	BS bandwidth, CR_{BS}	20 MHz
Number of SCs, M	15	SC bandwidth, CR_{SC}	5 MHz
Traffic load, $Load$	Fig. 3	δ	[0.5, 1.5]

where the first term is the aggregate valuation of the allocated resources, $(x^l_{n,m})^{\{-i\}}$, when MNO i does not participate at all in the auction. The second term is the aggregate valuation of the allocation $x^l_{n,m}$ of all MNOs other than i, when i participates in the auction. Next, we prove that our optimized auction mechanism possesses two important properties: 1) truthfulness and 2) individual rationality.

Proposition 2 (Truthfulness): The payment rule defined in (27) satisfies the truthfulness property.

Proof: The proof is given in Appendix B in the supplemental file. ■

Proposition 3 (Individual Rationality): The payment rule defined in (27) satisfies the individual rationality property, and all bidders are guaranteed to obtain nonnegative utility.

Proof: The proof is given in Appendix C in the supplemental file. ■

IV. PERFORMANCE EVALUATION

This section is composed of three parts. First, we explain the simulation scenario employed both for the multiobjective optimization and the system-level simulations. Second, we present the results regarding the estimation of the Pareto front for the multiobjective optimization solved by using the Matlab tools. Finally, we show a performance comparison between the proposed scheme and two state-of-the-art schemes with the development of a custom-made C simulator.

A. Simulation Scenario

The simulation scenario corresponds to a dense HetNet deployment, such as a university campus or an urban area. More specifically, our scenario focuses on a cell served by the BSs of $N = 5$ MNOs and $M = 15$ SCs that cover the whole cell area. In our experiments, we consider various scenarios, wherein the MNOs have different traffic volumes (i.e., ρ), different bidding strategies (i.e., nontolerant, linear, and tolerant), different cost requirements (i.e., z), and different bidding levels (i.e., L). The system-level simulations are based on Monte Carlo experiments, and the presented results focus on the night zone for the duration of one year.[5] The set of parameters is provided in Table I.

To assess the performance of our scheme, we compare the proposed multiobjective auction-base switching-off strategy (referred to as MAS), to two benchmark solutions: 1) an auction-based switching-off scheme, wherein the income of the

[5]Note that the results are calculated for the case of one macro cell, but they can be easily extended to extended configurations. Furthermore, we consider the period of one year since the yearly traffic is considered stable [30].

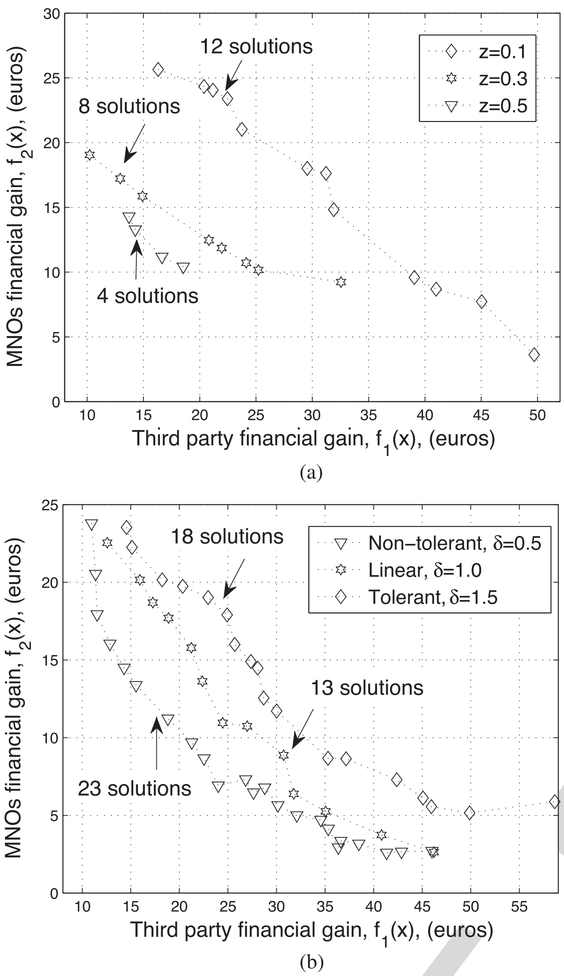

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Fig. 6. Estimation of Pareto front solutions. (a) Estimated Pareto front for multiple MNOs' requirements, $L = 2$ and linear bidding strategy. (b) Estimated Pareto front for multiple bidding strategies, $L = 2$, and $z = 0.1$.

third party is the unique objective to be maximized (referred as ISO) [17]; and 2) a baseline scenario with full operational topology (FOT), where none of the BSs is switched off.

B. Estimation of the Pareto Front

Here, we present the Pareto front analysis. In this set of experiments, we assume that all operators have the same traffic volume equal to the maximum possible traffic load, i.e., $\rho_n = 1$. In addition, we assume that each MNO submits three different bids, corresponding to $L = 2$, to the third party.

Fig. 6 shows the Pareto front solutions achieved by solving the proposed multiobjective problem for different minimum financial gains with the same bidding strategy [see Fig. 6(a)] and different bidding strategies with the same minimum profit requirement [see Fig. 6(b)]. In both figures, the third party's annual financial gain that can be attained by leasing its resources to one MNO is represented in the x-axis, and the annual economic profits of one MNO are given in y-axis.

In Fig. 6(a), the set of optimal solutions is shown for the linear bidding strategy. Note that the stochastic search performed by means of the metaheuristic algorithm succeeds in estimating a Pareto front for the given parameters of the studied problem. As expected, in all the different cases, the higher the third party's income $(f_1(\mathbf{x}))$, the lower the financial gain of the MNOs $(f_2(\mathbf{x}))$. Thus, the Pareto front is monotonically decreasing, meaning that the improvement of one objective leads to the deterioration of the other objective, and there is no feasible global solution maximizing all the objectives. A second observation relies on the motivation of the MNOs to maximize their economic gains, which is a fact that can be explored through the parameter z that reflects the requirements of the minimum profit gain, denoted in (11). As it is plotted in the figure, the greedy behavior of the MNOs for higher cost gains $(z = 0.5)$ leads to lower income for the third party and, at the same time, a lower number of achievable solutions. This result is of significant importance since a greedy behavior from the MNOs' perspective will produce lower bids that may not be accepted by the third party; thus, the MNOs will not be able to offload their whole traffic. The selection of a proper value of the parameter z helps the operators to decide whether it is profitable for them to bid by taking into account their financial needs, and by observing Fig. 6(a), we conclude that lower values of z lead to higher income for the two involved parties. To provide further insights for our approach, let us also highlight that, in a realistic scenario with a large number of macro BSs, the cost gains for the MNOs and the third party are significantly higher. For example, by applying the proposed switching off technique to the central area of London where an MNO may have up to 500 deployed BSs [31], the economic gains may reach up to $\sim$12.500 € for the MNO and up to $\sim$25.000 € for the third party.

In continuation, Fig. 6(b) illustrates the Pareto front by examining different bidding strategies for the case of $z = 0.1$. Again, we observe that the attained solutions are decreasing monotonically. Moreover, as we see, the more tolerant the bidding strategy of the MNOs, the higher financial gains for the involved parties. This important insight can be easily explained by taking into account the fact that a nontolerant MNO is more greedy; thus, it requests more capacity for the same bids with respect to a tolerant MNO, as shown in Fig. 5. As a result, the third party may lose its incentive to lease the bandwidth, and the economic benefits will be reduced for the MNOs and the SC network. It is noted that the tolerant bidding strategy offers better solutions due to the leasing of more resources and the switching off of higher number of BSs, whereas the linear bidding strategy implies an intermediate solution between the extreme cases. Hence, along with the minimum guaranteed profit, the bidding strategy is also an important indicator that affects the decision of MNOs on bidding.

C. Numerical Results

Here, the performance results with regard to telecommunication-oriented (network throughput and energy efficiency) and cost-oriented (annual cost and income gains) metrics are shown. In this set of experiments, we study a more realistic scenario, where the MNOs have different traffic volumes and, thus, different requirements and outcomes, when our proposed algorithm is applied. According to recent studies

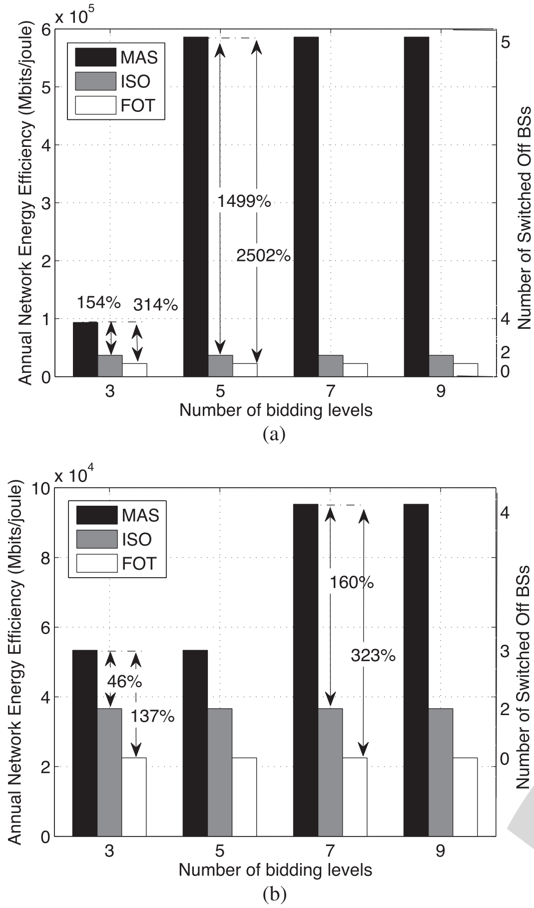

Fig. 7. Annual energy efficiency for $z = 0.1$ and different bidding strategies. (a) Tolerant bidding strategy. (b) Nontolerant bidding strategy.

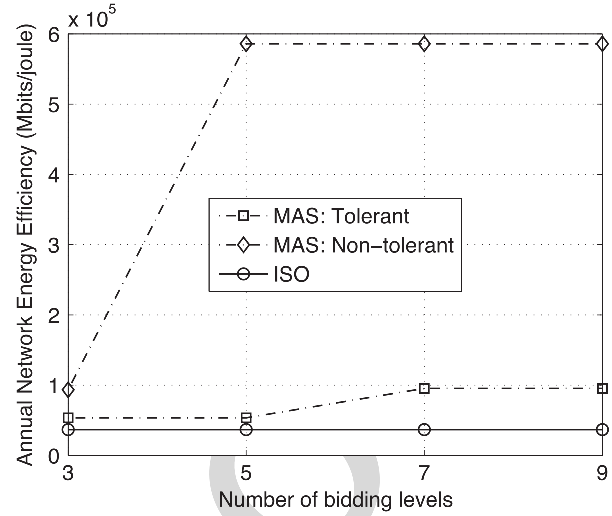

Fig. 8. Annual energy efficiency for different bidding levels and strategies.

[18], in most European countries, there are usually up to two telecommunication companies holding the major part of the market share, up to two smaller operators serving an intermediate portion of the users, and finally, up to one smaller MNO with a very small slice of the market. By exploiting these interesting findings, we consider the scenario in which two MNOs (i.e., BS_1 and BS_2) are fully loaded ($\rho_1 = \rho_2 = 1.0$), two operators (i.e., BS_3 and BS_4) have relatively lower traffic with $\rho_3 = \rho_4 = 0.7$, and the fifth MNO (denoted by BS_5) has very low traffic ($\rho_5 = 0.3$). The results presented in the following are calculated for an operating point on the Pareto front that is assumed to satisfy all the involved parties in the auction. We would like to highlight that the selection of a solution among the Pareto front solutions can be either derived through agreements between the involved parties or another distinguished entity may select it.

1) Telecommunication Metrics: Fig. 7 presents the total network energy efficiency versus L for tolerant [see Fig. 7(a)] and nontolerant [see Fig. 7(b)] bidding strategies. The number of switched-off BSs of every algorithm is also shown in the plot (right y-axis), along with the percentage gains in terms of energy efficiency of our approach compared with the state-of-the-art works. First, we observe that the energy efficiency achieved by the MAS scheme increases with the number of levels for tolerant and nontolerant bidding since the biggest variety of the proposed bids (higher number of levels) implies a higher number of choices for the resource allocation. Another important remark is that MAS significantly outperforms the baseline scenario, FOT, (where no BS is switched off), and the ISO algorithm. The better performance of our proposal in terms of energy efficiency is justified by the higher number of switched-off BSs as this is highlighted also in the plots. As we have already mentioned in Section III-C, the goal of our proposal lies in maximizing the energy efficiency, an objective neglected in the auction-based works of the literature, whereby only the maximization of the third party's income was considered. Comparing the behavior of our algorithm in the two figures, it can be observed that the tolerant bidding strategy achieves more considerable gains with respect to the nontolerant bidding, mainly due to the deactivation of many underutilized BSs in the network. These results emphasize the role of the bidding strategy and the number of bidding levels on the achievable energy efficiency, thus providing the necessary insights to the MNOs to select the most appropriate strategy based on their interests. In Fig. 8, the conclusions of Fig. 7(b) and (a) are better illustrated since the comparison between the three schemes and the different bidding strategies is more clearly shown. Finally, we should mention that the results of linear bidding are not shown here for simplicity, given that the achieved gains range between the two aforementioned cases.

Along with the total network energy efficiency performance, it is interesting to study the individual energy efficiency gains of the different MNOs. To that end, the individual gains for the specific (but representative) case of $z = 0.1$ and the two different bidding strategies are quantified in Table II, where interesting conclusions can be extracted. In particular, independently of the bidding strategy and the number of L, the ISO scheme is beneficial only for the group of operators that switch off their BSs, who are always the same (MNO_1 and MNO_2), whereas the rest of the operators always keep their BSs active. More specifically, the MNOs that switch off their BSs theoretically achieve infinite energy efficiency, as they

TABLE II
OPERATOR ENERGY EFFICIENCY (X 10^4 Mbits/Joule) WITH RESPECT TO THE FOT SCHEME FOR $z = 0.1$

	Tolerant bidding					Non-tolerant bidding				
Algorithm	MNO_1	MNO_2	MNO_3	MNO_4	MNO_5	MNO_1	MNO_2	MNO_3	MNO_4	MNO_5
MAS-L = 3	∞	3	∞	∞	∞	∞	3	2.2	∞	∞
ISO-L = 3	∞	∞	2.2	2.2	1	∞	∞	2.2	2.2	1
MAS-L = 7	∞	∞	∞	∞	∞	∞	3	∞	∞	∞
ISO-L = 7	∞	∞	2.2	2.2	1	∞	∞	2.2	2.2	1

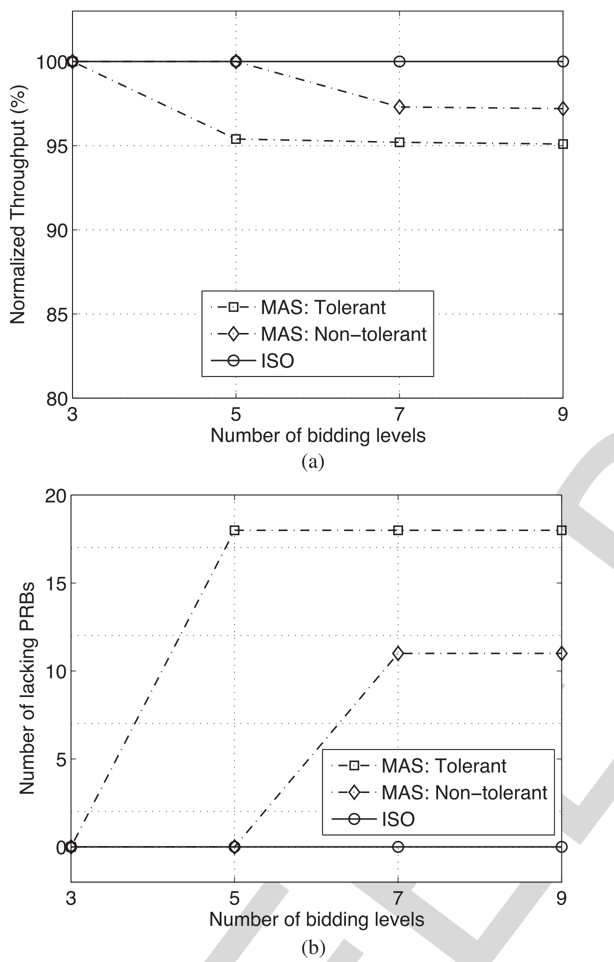

Fig. 9. (a) Normalized throughput for different bidding levels and strategies. (b) Number of lacking PRBs.

have their traffic served at zero energy cost, whereas the active operators serve their own traffic without improving their situation. The proposed MAS eliminates this unfairness by offering the chance to more MNOs to switch off their BSs, providing them with extra incentives to participate in the auction. The individual gains are remarkable of our proposal for both the MNOs and the whole network.

Despite the importance of the energy efficiency results, the deactivation of the BSs in the network and the traffic offloading to the SCs potentially implies loss of connections. To that end, we study the normalized throughput that represents the percentage of served connections in the system. In Fig. 9(a), it can be observed that, as the number of switched-off BSs increases, the MAS approach experiences small losses (around 5% and 3% for tolerant and nontolerant bidding, respectively). The degraded performance is explained by the high number of deactivated BSs, leading to the service of all the traffic mainly by the SC network (since at most one BS remains active). The MNOs are able to decide whether the throughput performance can be sacrificed to achieve energy efficiency, or even small losses are prohibitive (thus, a tolerant strategy is not acceptable). The results in terms of lacking PRBs are given in Fig. 9(b). As it is observed, a larger number of PRBs are lacking, when the MAS strategy is applied. In our case, there are different reasons for the degraded throughput performance. The unserved users exist because either lower bids (thus, fewer PRBs) are selected or the overall PRBs are not adequate for the total offloaded traffic. However, the impact on the throughput is negligible, as it was shown in Fig. 9(a).

2) Cost Metrics: The total annual network cost and the individual annual gains for the operators and the third party, compared with the state-of-the-art algorithm and having as a benchmark the FOT scheme, are presented in Figs. 10 and 12, respectively.

The annual network cost is given versus the different number of bidding levels and for the tolerant [see Fig. 10(a)] and nontolerant [see Fig. 10(b)] bidding strategies, respectively. The total network cost is the sum of the average cost of all MNOs and the third party for the operation of all infrastructures (i.e., the active BSs and SCs). The first observation is that the network cost is the same for level pairs ($l = 3$ and $l = 5$) and ($l = 7$ and $l = 9$) for the MAS algorithm, due to the number of switched-off BSs that is the same for the two cases. The MAS scheme achieves a considerable reduction up to 94% and 96% for tolerant bidding, when compared with ISO and FOT schemes, respectively. For the case of nontolerant bidding strategy, the cost reduction is lower. This result is explained by the fact that MNOs are more greedy, and in their attempt to increase their economic gains, they do not offer high bids for the requested capacity. As a consequence, the third party does not accept the allocation of resources to low prices, and some BSs may not be switched off. Concerning the ISO scheme, we observe that the total annual cost is not affected by the different bidding levels since, in ISO auction, only one bid is offered based on the maximum traffic expectations, and fewer BSs are deactivated. A clear comparison between MAS, for tolerant and nontolerant bidding, and ISO is given in Fig. 11, where the annual network cost behavior is highlighted.

The individual revenue of each MNO and the third party is plotted in Fig. 12. We may observe that, similar to the energy efficiency gains, the ISO scheme provides financial gains only to particular operators (MNO_1 and MNO_2) and particularly to

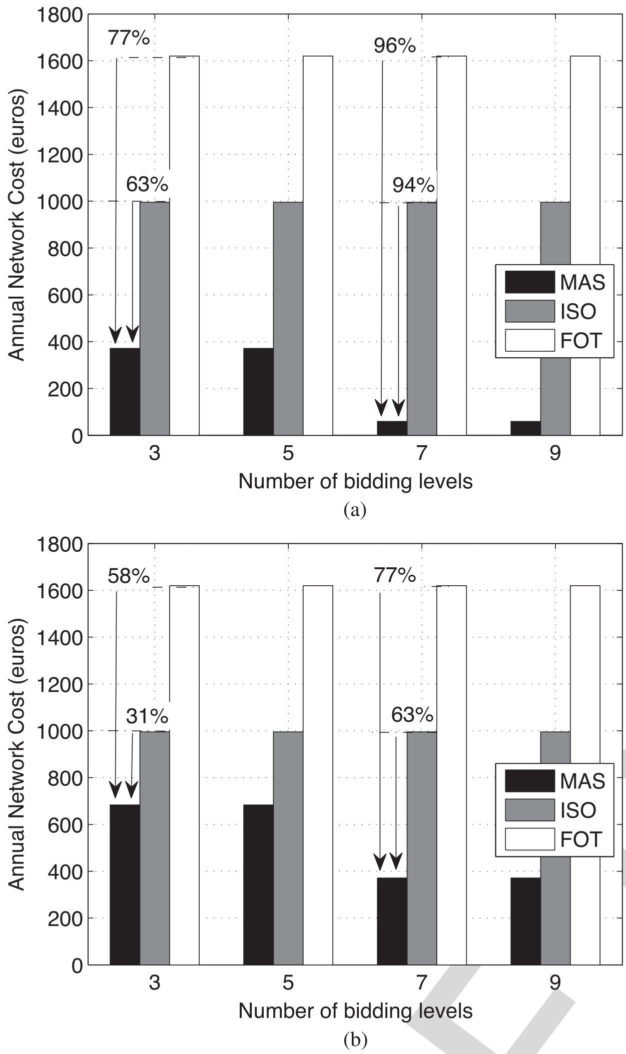

Fig. 10. Annual network cost for $z = 0.1$ and different bidding strategies. (a) Tolerant bidding strategy. (b) Nontolerant bidding strategy.

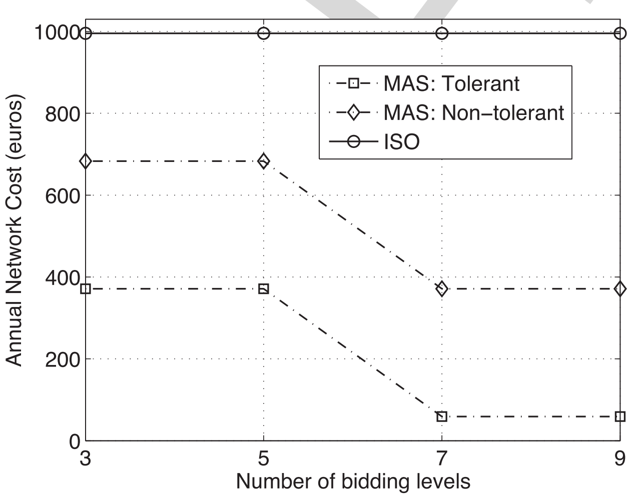

Fig. 11. Annual network cost for different bidding levels and strategies.

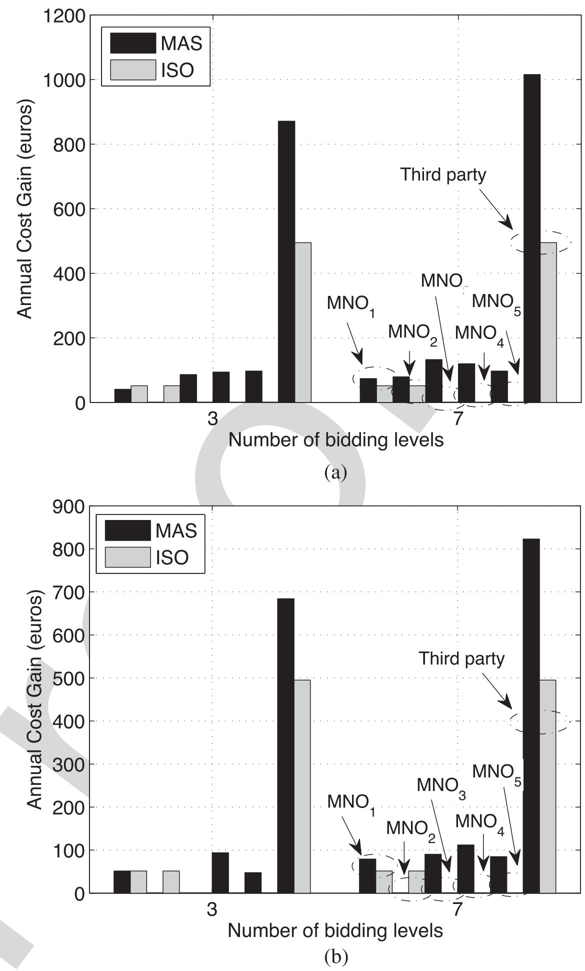

Fig. 12. Annual cost gain for $z = 0.1$ and different bidding strategies. (a) Tolerant bidding strategy. (b) Nontolerant bidding strategy.

the MNOs that switch off their networks, whereas the economic gains of the remaining operators are zero compared with the FOT scheme since these MNOs keep their BSs active and serve their own traffic without having any benefit from the auction. On the other hand, for the proposed MAS approach, more operators are able to have economic benefits, independently of the particular number of levels. Furthermore, as the number of bidding levels increases, the MAS algorithm achieves higher financial gains for the operators due to the higher number of combinations of bids offered. In addition, for the tolerant bidding strategy [see Fig. 12(a)], the economic gains are higher compared with the nontolerant behavior [see Fig. 12(b)].

D. Discussion

Based on the analysis in Sections IV-B and IV-C, we have shown that the proposed MAS scheme outperforms the state-of-the-art approaches in terms of energy efficiency (network and individual), annual network cost, and individual cost gains. In addition, it achieves balanced results for the MNOs with respect to the individual energy efficiency and cost gains. Furthermore, through a performance assessment, we have identified the significance of the bidding behavior, the number of levels, and parameter z. In particular, better performance results are attained in terms of energy efficiency, aggregate network cost, and individual cost gains, when a higher number of levels are chosen and through tolerant bidding. Moreover, higher values of z achieve lower gains for both the MNOs and the third party. Finally, although minor losses may appear in terms of throughput, the attained benefits with respect to energy efficiency, individual and network cost gains are remarkable and are adequate for giving the necessary incentives to the MNOs and the third party to apply the proposed auction-based switching-off strategy.

V. Conclusion

In this paper, motivated by the low BS utilization during the night and the coexistence of multiple MNOs and third-party SCs in the same area, we proposed a novel auction-based offloading and switching-off algorithm that achieves energy savings and cost reduction by encouraging MNOs to offload their traffic and switch off the redundant BSs. Moreover, by employing auction tools and novel bidding strategies, we introduced a switching-off scheme that allows the MNOs to reduce their expenditures. The proposed scheme has been evaluated in terms of energy efficiency and cost metrics for various conditions (different bidding levels and behaviors). The results have shown that our proposal can significantly improve the network energy efficiency, guaranteeing at the same time the throughput. Regarding the financial costs/gains, the proposed scheme provides higher cost benefits and fairness compared with the state-of-the-art algorithms. It provides also interesting insights concerning the rules and behaviors that the MNOs should follow when they participate in an auction strategy. The study of other schemes for the solution of the problem (such as backwards induction) and the potential trade-offs would be interesting research line for future works.

References

[1] "Cisco visual networking index: Global mobile data traffic forecast update," Cisco, San Francisco, CA, USA, pp. 2014–2019, Feb. 2015.
[2] X. Bao, Y. Lin, U. Lee, I. Rimac, and R. R. Choudhury, "Dataspotting: Exploiting naturally clustered mobile devices to offload cellular traffic," in *Proc. IEEE INFOCOM*, Apr. 2013, pp. 420–424.
[3] "Nokia networks: Solutions," Nokia, Espoo, Finland, 2015. [Online]. Available: http://networks.nokia.com/portfolio/solutions/heterogeneous-networks
[4] L. Gao, G. Iosifidis, H. Jianwei, and L. Tassiulas, "Economics of mobile data offloading," in *Proc. IEEE Workshop INFOCOM*, Apr. 2013, pp. 3303–3308.
[5] W. Dong *et al.* "iDEAL: Incentivized dynamic cellular offloading via auctions," in *Proc. IEEE INFOCOM*, Apr. 2013, pp. 755–763.
[6] S. Paris, F. Martignon, I. Filippini, and A. Capone, "A truthful auction for access point selection in heterogeneous mobile networks," in *Proc. IEEE ICC*, Jun. 2012, pp. 3200–3205.
[7] X. Zhuo, W. Gao, G. Cao, and S. Hua, "An incentive framework for cellular traffic offloading," *IEEE Trans. Mobile Comput.*, vol. 13, no. 3, pp. 541–555, Mar. 2014.
[8] G. Fettweis and E. Zimmermann, "ICT energy consumption—trends and challenges," in *Proc. WPMC*, Sep. 2008, pp. 1–4.
[9] G. Auer *et al.*, "How much energy is needed to run a wireless network?" *IEEE Wireless Commun.*, vol. 18, no. 5, pp. 40–49, Oct. 2011.
[10] F. Han, Z. Safar, and K. J. R. Liu, "Energy-efficient base-station cooperative operation with guaranteed QoS," *IEEE Trans. Commun.*, vol. 61, no. 8, pp. 3505–3517, Aug. 2013.
[11] E. Oh, K. Son, and B. Krishnamachari, "Dynamic base station switching-on/off strategies for green cellular networks," *IEEE Trans. Wireless Commun.*, vol. 12, no. 5, pp. 2126–2136, May 2013.
[12] A. Bousia, E. Kartsakli, L. Alonso, and C. Verikoukis, "Dynamic energy efficient distance-aware base station switch on/off scheme for LTE-Advanced," in *Proc. IEEE GLOBECOM*, Dec. 2012, pp. 1532–1537.
[13] A. Bousia, E. Kartsakli, A. Antonopoulos, L. Alonso, and C. Verikoukis, "Game theoretic infrastructure sharing in multi-operator cellular networks," *IEEE Trans. Veh. Technol.*, DOI: 10.1109/TVT.2015.2445837, to be published. AQ5
[14] J. Bartelt, A. Fehske, H. Klessig, G. Fettweis, and J. Voigt, "Joint bandwidth allocation and small cell switching in heterogeneous networks," in *Proc. IEEE VTC—Fall*, Sep. 2013, pp. 1–5.
[15] Y. S. Soh, T. Q. S. Quek, M. Kountouris, and H. Shin, "Energy efficient heterogeneous cellular networks," *IEEE J. Sel. Areas Commun.*, vol. 31, no. 5, pp. 840–850, May 2013.
[16] M. H. Alsharif, R. Nordin, and M. Ismail, "A review on intelligent base stations cooperation management techniques for greener LTE cellular networks," *J. Commun.*, vol. 9, no. 12, pp. 937–945, Dec. 2014.
[17] S. Paris, F. Martignon, I. Filippini, and L. Chen, "A bandwidth trading marketplace for mobile data offloading," in *Proc. IEEE INFOCOM*, Apr. 2013, pp. 430–434.
[18] M. A. Marsan and M. Meo, "Network sharing and its energy benefits: A study of European mobile network operators," in *Proc. IEEE GLOBECOM*, Dec. 2013, pp. 2561–2567.
[19] "Small cell market status," Small Cell Forum, U.K., Feb. 2013. [Online]. Available: http://www.smallcellforum.org/resources-reports
[20] "3rd generation partnership project; technical specification group services and system aspects; telecommunication management; study on Energy Savings Management (ESM) (Release 10)," Third-Generation Partnership Project, Sophia Antipolis Cedex, France, Tech. Rep., 3GPP TR 32.826, V10.0.0, Mar. 2010.
[21] "Mobile traffic forecasts 2010–2020 Report," UMTS Forum, London, U.K., Jan. 2011.
[22] V. Krishna, *Auction Theory*. San Diego, CA, USA: Academic, 2010.
[23] A. Bousia, E. Kartsakli, A. Antonopoulos, L. Alonso, and C. Verikoukis, "Sharing the small cells for energy efficient networking: How much does it cost?" in *Proc. IEEE GLOBECOM*, Dec. 2014, pp. 2649–2654.
[24] Y. Sawaragi, I. Hirotaka, and T. Tanino, *Theory of Multiobjective Optimization*, 1st ed. New York, NY, USA: Academic, 1985.
[25] T. Weise, *Global Optimization Algorithms—Theory and Application*, 2nd ed. Hefei, China: Thomas Weise, 2009. [Online]. Available: http://www.it-weise.de/
[26] R. L. Carraway, T. L. Morin, and H. Moskowitz, "Generalized dynamic programming for multicriteria optimization," *Eur. J. Oper. Res.*, vol. 44, no. 1, pp. 95–104, Jan. 1990.
[27] H. G. Beyer and K. Deb, "On self-adaptive features in real-parameter evolutionary algorithms," *IEEE Trans. Evol. Comput.*, vol. 5, no. 3, pp. 250–270, Jun. 2001.
[28] C. A. Coello, G. B. Lamont, and D. A. Van Veldhuizen, *Evolutionary Algorithms for Solving Multi-Objective Problems*, ser. Genetic and Evolutionary Computation, 2nd ed. Berlin, Germany: Springer-Verlag, 2007.
[29] L. M. Schmitt, "Theory of genetic algorithms II: Models for genetic operators over the string-tensor representation of populations and convergence to global optima for arbitrary fitness function under scaling," *Theoretical Comput. Sci.*, vol. 310, pp. 181–231, 2004.
[30] "Ericsson mobility report: On the pulse of the networked society," Ericsson, Stockholm, Sweden, Tech. Rep. Nov. 2014.
[31] "Sitefinder: Mobile Phone Base Station Database," Ofcom, London, U.K., Mar. 2015. [Online]. Available: http://sitefinder.ofcom.org.uk/search

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