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Revenue Maximization Through Cell Switching and Spectrum Leasing in 5G HetNets

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ABSTRACT Even though dynamic cell switching is a prominent approach for energy optimization in heterogeneous wireless communication networks, it results in spectrum under-utilization as the spectrum originally occupied by the base stations that are turned off remain dormant. In order to make the businesses of primary network (PN) operators, who hold the spectrum license, more profitable and sustainable as well as to avoid spectrum under-utilization, this dormant spectrum can be leased to the secondary network (SN) operators who cannot afford to purchase the spectrum license. In this study, first, the cell switching problem, which solely focuses on the amount of energy saved, is translated to a problem of revenue maximization by including the spectrum leasing concept and converting the energy saving to monetary saving from reduced electricity bills. In this regard, two spectrum demand scenarios are considered for the SN operator: delay tolerant (DT), for non-real time applications, and non-delay tolerant (NDT), for real time applications. Then, a cell switching and spectrum leasing framework based on simulated annealing algorithm is developed to maximize the revenue of the PN while respecting the quality-of-service constraints. The simulation results reveal that the DT spectrum demand is more beneficial to both PN and SN operators as it results in greater revenue for the former while the latter is able to access more spectrum to meet higher service demands. This finding suggests that if the application can tolerate delays, then it makes more sense for both PN and SN to adopt the DT scenario. In addition, it is observed that the performance of the proposed framework is very close to that of the optimal solution with a significant reduction in the computation complexity.

INDEX TERMS 5G, HetNet, cell switching, energy efficiency, green communications, spectrum leasing, simulated annealing algorithm.

I. INTRODUCTION

In order to achieve enhanced data transmission as a challenge, mobile network operators (MNOs) are constantly facing the demand for capacity improvement. This is due to increase in the number of connected devices, increasing use of data hungry applications, such as online gaming and multimedia services, as well as other emerging use cases including virtual

and augmented reality, driver-less cars, etc [1]. In addition, with the proliferation of Internet of things (IoT) devices where virtually everything is connected to the Internet, the demand for more capacity would further escalate [2].

One of the major approaches for enhancing network capacity to meet the ever increasing data demands in 5G is the introduction of network densification [3], which involves the deployment of massive number of small base stations (SBSs), including remote radio head (RRH), micro, pico, and femto, under the coverage of macro base stations (MBSs),

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by employing the principle of spatial frequency reuse. However, this comes at a cost of increased network energy consumption (as 5G also targets to be 100 times more energy efficient than 4G networks) [4]. Also, with 6G network targeting higher capacity and data rates due to emerging use cases, the network densification would further increase in 6G [5]. This means that the energy consumption of the network would further escalate if not properly managed. To tackle the problem of increased energy consumption owing to capacity expansion through network densification, the most common approach is to implement dynamic network operation; i.e., the base stations (BSs) are only available when needed. This can be achieved via dynamic cell switching and traffic offloading [6].

In dynamic cell switching approach, the BSs (which accounts for about 50% - 60% of the total power consumption of the radio access networks (RAN)) [4] are turned off when they are not serving any user demand or have very few users connected to them, while the traffic of the BSs that are turned off are transferred to the neighbouring BSs or MBSs. This ensures that the energy consumption of the network scales with the capacity utilization thereby enhancing the energy efficiency of the network. Dynamic cell switching has the advantage of minimizing energy consumption of the network which translates to cost savings or additional revenue on the side of the mobile network operators (MNOs) due to reduction in the expenditure on energy purchase. It also results in reduced greenhouse gas emission, as most of the energy used to power the BSs are from fossil fuels, thus ensuring environmental sustainability [7].

One of the major drawbacks of dynamic cell switching is that the spectrum allocated to the switched off BSs remains dormant during the period that they are inactive, resulting in spectrum under-utilization. Such dormant spectrum can be leased to smaller network operators (also known as secondary networks (SN) operators) who require a smaller amount of spectrum for their data transmission and cannot afford to purchase a spectrum license like the major network operators (also known as primary network (PN) operators). This is because spectrum is normally auctioned by the telecommunication regulatory body in each country (e.g., Office of Communications (Ofcom) in the UK) at a very expensive rate. Spectrum leasing results in enhanced spectrum utilization and additional revenue to the PN operators, since it has been observed that the licensed spectrum is not always fully utilized most of the time [8]. The spectrum purchased by the SN from the PN can be used to provide data services which are delay tolerant (DT) such as meter readings, health information from wearables, etc., and do not require real-time data transmission. It can also be used to provide non-delay tolerant (NDT) services such as location and traffic update services, voice calls, etc., which require real-time data transmission for quick decision making. Therefore, the PN operator can gain revenue both from energy cost savings due to dynamic cell switching and from leasing the dormant spectrum of the BSs that are turned off to the SN.

Several approaches have been proposed in the literature for implementing dynamic cell switching in mobile cellular networks [9]–[16]. These methods comprise analytical, heuristic and machine learning-based approaches. Similar optimization techniques have also been proposed for spectrum leasing [17]–[22]. However, very few research works have considered both cell switching and spectrum leasing for maximizing the revenue of the PN [23], [24], even though only a homogeneous network deployment scenario as well as a fixed electricity and spectrum pricing policy were considered, thereby making their work quite simplistic.

In order to fill in the above-mentioned gaps in the literature, two different perspectives should be taken into consideration. First, the cell switching and spectrum leasing problems should be considered together in order to have a holistic view. Therefore, in this paper, we first combine the cell switching and spectrum leasing concepts, and produce a joint optimization problem. To do this, we converted the energy saving via cell switching to its monetary equivalent, that is, the reduction in the energy bills, so that the energy saving and revenue can be combined. This enables us to model the joint optimization problem in a way that a single objective function can be obtained, since the outputs of both energy saving and spectrum leasing are monetary. Second, such holistic view should be tested in a more realistic and complex scenario to verify its applicability and feasibility. For this purpose, we created a heterogeneous network (HetNet) scenario with different types of SBSs. Moreover, in addition to classical fixed pricing policy, we also adopted a dynamic pricing policy for both electricity and spectrum. These two components of the considered scenario (i.e., diverse set of SBSs and dynamic pricing policy) make it not only more realistic but also more challenging, given that each type of SBS has different characteristics and the overall system becomes quite dynamic (e.g., the loads of BSs and the prices of electricity and spectrum change at each time slot).

The solution to this problem is non-trivial as it involves trying different options out of a large set of possibilities. The optimal solution is the exhaustive search (ES) approach because it tries all the possible options before selecting the best one; however, it results in a huge computational overhead especially when the number of SBSs deployed in the network becomes very large.

A. CONTRIBUTIONS

In this paper, we propose a cell switching and spectrum leasing framework to maximize the revenue of the PN. The proposed algorithm is able to learn the optimal cell switching and spectrum leasing policy that would result in maximum revenue for the PN while ensuring that the QoS of the PN is maintained. The proposed framework is implemented locally at each MBS since they are responsible for controlling the SBSs under their coverage. The following are the contributions of this work:

- We formulate the problem as a binary integer programming problem and develop a cell switching and spectrum

leasing framework using the SA algorithm to determine the optimal policy that maximizes the revenue of the PN while ensuring that the QoS is maintained.

- We consider a HetNet comprising four different types of SBSs, which makes the network scenario more complex and realistic compared to the previous works that considered only homogeneous scenario.
- We consider two electricity and spectrum pricing policies: 1) fixed and 2) dynamic policy, in order to study the effects of constant and varying electricity and spectrum prices on the maximum revenue of the PN, as both could be the cases faced in real systems. For the dynamic pricing policy, both DT and NDT spectrum demand scenarios are also investigated.
- In addition to the ES algorithm, two benchmark solutions are also developed for comparison with the proposed framework.
- A complexity comparison of the proposed method with that of the ES is carried out to highlight the advantage of the proposed framework.
- Finally, in order to capture the realistic behaviour of the network, the performance of the proposed framework is evaluated using real data comprising call detail records (CDR) of Milan city via extensive simulations, and the result obtained is compared with benchmarks.

The remaining part of this paper is organized as follows: In Section II we review the related literature, while in Section III the system model is comprehensively presented. The proposed SA algorithm based framework for cell switching and spectrum leasing is discussed in Section IV, followed by the performance evaluation in Section V. Section VI concludes the work.

II. RELATED WORKS

Dynamic cell switching techniques are the most commonly employed methods for optimizing energy consumption in cellular networks because they are the cheapest to implement and require minimal changes to network architecture [4]. These techniques result in significant energy savings compared to other methods such as cell zooming, bandwidth adaptation, sectorization, etc [6], [7].

The authors in [9] proposed a SBS switching scheme to minimize the energy consumption in a HetNet based on stochastic geometry. In [10] the authors considered the problem of SBS power control and user association in HetNets and proposed a heuristic algorithm to determine the switching pattern of redundant SBSs during periods of low traffic. In [11], a user association and cell switching algorithm based on belief propagation was developed to maximize the energy efficiency (EE) of a HetNet by switching off BSs with few users while transferring serving users to neighbouring BSs. In [12], the authors proposed an SBS switching mechanism based on particle swarm optimization to minimize the energy consumption of a HetNet without violating QoS constraints. An SBS switching mechanism for EE optimization in HetNet

using genetic algorithm was proposed in [13] while respecting QoS constraints.

The authors in [14] proposed a reinforcement learning (RL) based cell switching approach to optimize the energy efficiency as well as the CO₂ emission in a HetNet. A cell switching and traffic offloading scheme for energy optimization in ultra-dense network using artificial neural network was proposed in [15]. The authors in [16] developed a scalable RL based cell switching framework using state-action-reward-state-action (SARSA) algorithm with value function approximation to determine the optimal switching policy that would minimize the energy consumption in an ultra dense network while ensuring that the QoS of the network is maintained. Even though dynamic cell switching results in significant energy savings, it also results in spectrum under-utilization as the spectrum that was originally allocated to the SBSs that are switched off remain dormant when they are inactive. These dormant spectrum can be exploited via spectrum leasing operations.

As regards spectrum leasing, three major reasons for spectrum leasing have been advanced in literature [25]: i) For monetary gains, ii) to maximize transmission rates, and iii) to reduce the energy consumption of primary users (PUs). In the first case, the PN leases some of its spectrum to the SN at a cost in order to generate additional revenue. In the second case, the PN shares some of its spectrum to the SN in exchange for assistance in data transmission, thereby enhancing the data rates of the PUs. In the third case, the secondary users (SUs) act as a relay to the PUs thereby reducing the transmission distance between the PUs and the BSs which leads to energy savings in the PUs. In this work, we are interested in the first case that is spectrum leasing for monetary gains because we want to maximize the revenue of the PN.

In this regard, various research works using techniques such as game theory, matching theory, and machine learning techniques, etc., have been proposed [17]–[22]. The authors in [17] proposed a traffic-adaptive spectrum leasing scheme whereby the SUs are able to negotiate the duration of channel leasing with the PUs in order to ensure their continual utilization of the leased channel for the complete transmission of the data in their buffer. To achieve this objective, the average utilities of both the PN and SN were first formulated, after which a spectrum leasing agreement that is beneficial to both parties was developed using Stackelberg game model. The work in [19] proposed a joint optimization scheme for spectrum leasing and spectrum allocation using both Stackelberg game and matching theory. The proposed approach is able to determine the best price for leasing the spectrum as well as the best PU-SU pair while enhancing the spectral efficiency of the PUs and SUs. In [18], the authors considered a spectrum leasing problem between MNOs and mobile virtual network operators (MVNOs) using matching theory in order to maximize the utilities of both parties in terms of spectrum leasing cost and bandwidth allocation. Their goal is to find a suitable pairing between the MNOs and MVNOs that would maximize

the revenue of the MNOs as well as the bandwidth allocated to the MVNOs.

The work in [22] considered the problem of spectrum leasing optimization for cognitive radio network (CRN) transmission over TV white spaces. A neural network based solution was proposed to determine the optimal transmission policy that would result in minimal spectrum leasing cost while considering the QoS of the CRN. The works in [20] and [21] considered the problem of resource allocation and spectrum leasing in CRNs where the PUs lease part of their spectrum to the SUs in exchange for data transmission assistance from the SUs as well energy saving for the PUs. Joint cell switching and spectrum leasing has been considered in [23] and [24] to maximize the profit of both PN and SN as well as to minimize the energy consumption of PN. The authors in [23] considered a CRN comprising both PN and SN where the PN aims to reduce its energy consumption by turning off some BSs and transferring the users to the SN to maintain their QoS. In addition, the PN obtains revenue by leasing the free spectrum to the SN while the SN also gains revenue from the PN by charging a roaming price. A sub-optimal heuristic algorithm was developed to optimize the energy consumption of the PN by determining the set of BSs to switch off.

The novelty of this work is threefold: A low complexity, cell switching and spectrum leasing framework is proposed, which considers a HetNet scenario comprising different types of BSs as opposed to previous works in [23] and [24] that considered only homogeneous scenario comprising only one type of BS. Second, both fixed and dynamic electricity pricing and spectrum leasing policies, as well as delay tolerant (DT) and non-delay tolerant (NDT) spectrum demands, which are a better representation of what is obtainable in real systems. Thirdly, we avoided roaming charges by ensuring that only vertical traffic offloading between SBSs that are switched off and the MBS of the PN is considered, in order to minimize additional expenses and maintain the QoS of the network.

III. SYSTEM MODEL

A. NETWORK MODEL

The network model is presented in Fig. 1. Two types of networks are considered: First, the PN is a HetNet with control and data separated architecture (CDSA) [26] comprising multiple macro cells (MCs). Each MC consists of one MBS and several SBSs. The MBSs serve as control BSs, provide constant coverage and low data rate transmission. The SBSs are deployed within the coverage of the MBSs and serve as data BSs to provide high data rate transmissions in hot spot zones. The communication between MBS and SBSs are carried out in the control channels, which are separated from the data channels. Four types of SBSs—RRH, micro, pico and femto—are considered. Second, a SN is also assumed to operate in the same coverage area and the HetNet allows this SN to lease some unused spectrum whenever PN SBSs are put to sleep.

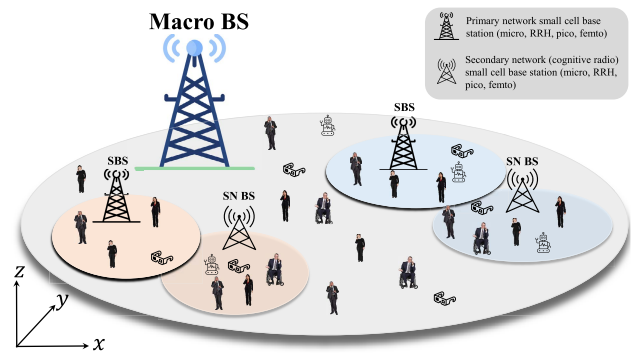


FIGURE 1. The PN comprises a MC which consists of an MBS and various types of SBSs and the SN comprises SN BSs. Note that the HetNet can include multiple MCs.

In this context, it is assumed that each SBS continuously monitors the activity of the SN BSs in their coverage area and reports the spectrum demand alongside their own traffic load to the MBS. The MBS then decides which set of SBSs to switch off in order to maximize the revenue of the PN based on the available radio resources in the MBS, the traffic loads of the SBSs, and the spectrum demanded by the SN's BSs without violating the QoS of the PN. This can be maintained by ensuring that the traffic load of the SBSs that are switched off are transferred to the MBS.

In this work, we assume that the traffic load of all users can be sustained by the network before cell switching and spectrum leasing is implemented, which means that the network has enough radio resources to support all users' traffic demands. However, when cell switching and spectrum leasing is implemented, we cannot guarantee that the network would have sufficient resources to handle the traffic load of all users any more. Hence, we define the QoS as the capacity of the network to sustain the traffic load of all the users after cell switching and spectrum leasing operation. This is referred to as coverage loss in [27].

Due to the CDSA employed, all the MCs are assumed to have similar deployment characteristics except for the number and composition of SBSs. In addition, they also function in a decentralized manner, with the MBS responsible for controlling the operations of all the SBSs in each MC. Hence, in this work, we considered only one MC comprising 12 SBSs, four of each type of SBSs, as a representation of other MCs within the network. Each primary network (PN) SBS, has a secondary network (SN) BS associated with it, bringing the total number of SN BSs considered to 12.

B. POWER CONSUMPTION OF HETNET

We adopt the BS power consumption model in [28], [29] for estimating the power consumption of the BSs in the HetNet. The total power consumption of the HetNet comprises sum of the power consumption of the MBS and that of all the SBSs under its coverage. The instantaneous power consumption of a BS, $P_{BS,t}$, at time t can be expressed as:

$$P_{BS,t}(\tau_t) = P_0 + \tau_t \zeta P_{tx}, \quad (1)$$

where P_o is the constant circuit power consumption, τ_t is the instantaneous traffic load of any BS at time t , ζ is the load dependent power consumption component and P_{tx} is the transmission power of the BS. It should be noted that the value of P_o , ζ , and P_{tx} is different for each type of BS (i.e., MBS, RRH, micro, pico, and femto).

As such, the instantaneous total power consumption of the HetNet, $P_{HN,t}$, at time t can be expressed as:

$$P_{HN,t}(\tau_t^{i,j}) = \sum_{i=1}^{M_m} \sum_{j=1}^{M_b} P_{BS,t}^{i,j}(\tau_t^{i,j}), \quad (2)$$

where $P_{BS}^{i,j}$ and $\tau_t^{i,j}$ denotes the power consumption and traffic load of the j^{th} BS in the i^{th} MC respectively, and $P_{BS^{i,1}}$ represents power consumption of the MBS in the i^{th} MC. M_m and M_b are the number of MCs within the HetNet and the number of BSs (including an MBS and SBSs) within an MC, respectively.

C. PRICING POLICY

Two kinds of pricing policies are considered for both the electricity and spectrum:

1) FIXED PRICING POLICY

The unit cost of electricity as well as that of the spectrum remains constant throughout the day, irrespective of the fluctuations in energy or spectrum demand.

2) DYNAMIC PRICING POLICY

The electricity and spectrum price varies according to the amount of electricity and spectrum demanded at different times of the day. The dynamic pricing model for electricity was adapted from [30], where the instantaneous electricity prices were obtained by multiplying the fixed price by a variable factor to indicate changes in the prices at different times of the day. For the dynamic spectrum price, we assumed that the spectrum prices follow the traffic demand pattern of the PN. However, these values are scaled with the fixed spectrum price such that: $C_{RB,t} = m \cdot C_{RB,F}$, where m is a time variable function that changes with the instantaneous traffic load, τ_t , i.e., $m = f(\tau_t)$, $C_{RB,t}$ and $C_{RB,F}$ are the dynamic and fixed spectrum price (i.e., cost per resource block (RB)). According to 3GPP [31], a RB is equivalent to 12 successive subcarriers, thus taking one subcarrier to be 15kHz, we consider one RB to be 180kHz. The dynamic electricity and spectrum pricing policies are presented in Fig. 2.

Under the dynamic spectrum pricing policy, two types of spectrum demand scenarios are considered:

- **Non-Delay Tolerant (NDT):** This scenario deals with applications such as location updates, voice calls, etc., that require real-time data transmission and cannot tolerate delay because of the sensitivity of the information and its requirement for quick decision making. For such applications, the SN has to demand for the spectrum as

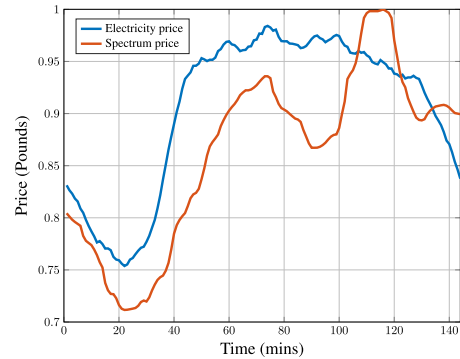


FIGURE 2. Dynamic electricity and spectrum pricing policy (normalized) for every 10 minutes over a 24 hours period.

soon as the need for data transmission arises, irrespective of the spectrum price.

- **Delay Tolerant (DT):** There are some other applications such as meter readings, feedback from wearables, etc., whose information may not be needed for real-time decision making and hence can tolerate some level of delay in data transmission. In these scenarios, the SN can decide to accumulate their service demands until the periods of the day where the spectrum price is cheapest, before transmission to save cost. In this work, the cheapest period is statistically decided only once and then the traffic is adjusted accordingly.

IV. PROBLEM FORMULATION

A specific time period T (in mins) is considered and it is then divided into equal time slots (in mins) with a duration of d (in mins). Then, we define an index vector t that stores the time slots in an order, such that $t = [1, 2, \dots, M_T]$, where M_T is the number of time slots and is given by $M_T = T/d$. The BSs of the PN are represented by $B_P^{i,j}$ while that of the SN by $B_S^{i,j}$. We view the problem from the PN perspective and formulate the revenue maximization problem by considering the revenue obtained from the combination of cell switching and spectrum leasing. Since the PN obtains its power supply from the grid, it can decide to turn off some SBSs during periods of low traffic to reduce their energy cost (i.e., gain some revenue from energy saving) and also lease the dormant spectrum to the SN in order to gain additional revenue.

3) REVENUE FROM CELL SWITCHING

The overall power consumption—the summation of the power consumption of all the BSs over all the time slots—when no cell switching is implemented (i.e., when all the BSs are on), P_{on} , can be expressed as:

$$P_{on} = \sum_{t=1}^{M_T} \sum_{i=1}^{M_m} \sum_{j=1}^{M_b} P_{BS,t}^{i,j}(\tau_t^{i,j}). \quad (3)$$

The overall power consumption—the summation of the power consumption of all the BSs over all the time

slots—when cell switching is implemented (i.e., when some BSs are turned off), P_{cs} , is given by:

$$P_{cs} = \sum_{t=1}^{M_T} \sum_{i=1}^{M_m} \sum_{j=1}^{M_b} [\Gamma_t^{i,j} P_{BS,t}^{i,j}(\tau_t^{i,j}) + (1 - \Gamma_t^{i,j}) P_{BS,s}^{i,j}], \quad (4)$$

where $P_{BS,s}^{i,j}$ is the power consumption of the BS when it is switched off (i.e., sleep mode power consumption of the BSs) $\Gamma_t^{i,j}$ denotes the on/off status of the $(i, j)^{th}$ BS at time t i.e.,

$$\Gamma_t^{i,j} = \begin{cases} 1, & \text{if } B_P^{i,j} \text{ is on} \\ 0, & \text{if } B_P^{i,j} \text{ is off,} \end{cases} \quad (5)$$

Since the MBS is always on, $\Gamma_t^{i,1} = 1, \forall t$.

Then, the overall power saving due to cell switching, P_{sv} can be expressed as:

$$P_{sv} = P_{on} - P_{cs}. \quad (6)$$

Therefore, the revenue due to energy saving, R_E , can be expressed as:

$$R_E = \sum_{t=1}^{M_T} P_{sv,t} \frac{T}{M_T} C_{e,t}, \quad (7)$$

where $C_{e,t}$ is the cost of electricity at time t , and $P_{sv,t}$ is the energy saving at time t .

4) REVENUE FROM SPECTRUM LEASING

The revenue due to spectrum leasing, (R_1), can be expressed as:

$$R_1 = \sum_{t=1}^{M_T} \sum_{i=1}^{M_m} \sum_{j=1}^{M_b} (1 - \Gamma_t^{i,j}) \min(\Psi_{S,t}^{i,j}, \Psi_{D,t}^{i,j}) C_{RB,t} \quad (8)$$

where $\Psi_{S,t}^{i,j}$ denotes the amount of spectrum (number of RBs) supplied by $B_P^{i,j}$, $\Psi_{D,t}^{i,j}$ denotes the amount of spectrum demanded by $\Psi_{S,t}^{i,j}$ from $B_P^{i,j}$ and $C_{RB,t}$ is the unit cost of spectrum (i.e., price per RB) at time t .

$B_P^{i,j}$ and $B_S^{i,j}$ are assumed to have the same capacity, which implies that $\Psi_{D,t}^{i,j} \leq \Psi_{S,t}^{i,j}$. Therefore, (8) can be simplified as:

$$R_1 = \sum_{t=1}^{M_T} \sum_{i=1}^{M_m} \sum_{j=1}^{M_b} (1 - \Gamma_t^{i,j}) \Psi_{D,t}^{i,j} C_{RB,t}. \quad (9)$$

5) TOTAL REVENUE

The total revenue of the PN, R_T can be expressed as:

$$R_T = R_E + R_1, \quad (10)$$

and substituting (7) and (9) in (10), we obtain:

$$\begin{aligned} R_T &= \sum_{t=1}^{M_T} P_{sv,t} \frac{T}{M_T} C_{e,t} + \sum_{t=1}^{M_T} \sum_{i=1}^{M_m} \sum_{j=1}^{M_b} (1 - \Gamma_t^{i,j}) \Psi_{D,t}^{i,j} C_{RB,t} \\ &= \sum_{t=1}^{M_T} \sum_{i=1}^{M_m} \sum_{j=1}^{M_b} (1 - \Gamma_t^{i,j}) \Psi_{D,t}^{i,j} C_{RB,t} + P_{sv,t} \frac{T}{M_T} C_{e,t}. \end{aligned} \quad (11)$$

Replacing (7) with (3) and (4) and simplifying (11), we get the closed form expression for the total revenue and is expressed as:

$$\begin{aligned} R_T &= \sum_{t=1}^{M_T} \sum_{i=1}^{M_m} \sum_{j=1}^{M_b} (1 - \Gamma_t^{i,j}) \\ &\times \left[\sum_{i=1}^{M_T} (P_{BS,t}^{i,j} - P_{BS,s}^{i,j}) \frac{T}{M_T} C_{e,t} + \Psi_{D,t}^{i,j} C_{RB,t} \right]. \end{aligned} \quad (12)$$

6) OPTIMIZATION OBJECTIVE

The revenue maximization objective function is the joint optimization of the revenue due to cell switching and spectrum leasing and can be expressed as:

$$\max_{\Gamma_t^{i,j}} R_T(\tau^{i,j}, \Gamma_t^{i,j}) \quad (13)$$

$$\text{s.t.} \quad \Upsilon^i = \hat{\Upsilon}^i, \quad \forall i, j, \quad (14)$$

$$\hat{\tau}^{i,1} \leq \tau_m^{i,1}, \quad \forall i, \quad (15)$$

$$\Gamma_t^{i,j} \in \{0, 1\}, \quad \forall i, j. \quad (16)$$

The constraints of (13) are explained in the following. The traffic demand, Υ^i , when all the BSs in the MC i are on (i.e., before traffic offloading) is computed as,

$$\Upsilon^i = \sum_{j=1}^{M_b} \tau^{i,j}, \quad \forall i. \quad (17)$$

To ensure QoS, the traffic of any SBS that is switched off will be transferred to MBS and therefore the actual traffic of MBS during the offloading process, denoted by $\hat{\tau}^{i,1}$ is equal to,

$$\hat{\tau}^{i,1} = \tau^{i,1} + \sum_{j=2}^{M_b} \tau^{i,j} (1 - \Gamma_t^{i,j}), \quad \forall i. \quad (18)$$

The traffic demand of the MC after traffic offloading, $\hat{\Upsilon}^i$ can be expressed as,

$$\hat{\Upsilon}^i = \hat{\tau}^{i,1} + \sum_{j=2}^{M_b} \tau^{i,j} \Gamma_t^{i,j}, \quad \forall i. \quad (19)$$

Therefore, (17) must be equal to (19) to satisfy the constraint in (14). We are assuming that MBS will be able to handle the traffic of all the switched off SBSs. On the other hand, if there is a maximum limit on the amount of traffic that the MBS can handle then we also have to introduce another constraint. For example, let $\tau_m^{i,1}$ denote the maximum traffic that MBS can serve in any time slot t . Then, we have the additional constraint in (15).

The solution to the problem in (13) is non-trivial as it involves deciding the optimal set of SBSs to turn off out of all the possible options, and then leasing their spectrum to the SN BSs in order to maximize the revenue of the PN. The optimal solution can be obtained from ES algorithm, however, the number of search spaces increases exponentially with the number of SBSs in ES, thereby

resulting in huge computational overhead. Hence, we resort to a less complex heuristic which considers a lesser search space and can give a sub-optimal solution with reduced computational complexity (lesser search spaces compared to ES).

V. PROPOSED FRAMEWORK

The aim of this paper is to determine the optimal cell switching and spectrum leasing strategy that would maximize the revenue of the PN without compromising the QoS of the network. Although ES always finds the optimal policy, it is computationally complex to implement because it has to sequentially search through all the possible cell switching and spectrum leasing combinations before deciding the optimal solution. As a result, in this work, we employ the SA algorithm which has lesser complexity since it involves lesser search spaces in finding the optimal solution. However, this algorithm is not always guaranteed to produce the optimal result as is the case with ES. In this regard, albeit being sub-optimal, through extensive simulations, we prove that the developed SA algorithm based solution produces almost the same results as the ES algorithm—especially when the network sizes are reasonable—with much less computational complexity, providing a promising trade-off between the performance and complexity.

A. SIMULATED ANNEALING (SA) ALGORITHM

The SA algorithm is a probability-based heuristic that deals with the annealing process in solid materials. The working principle of SA algorithm involves mimicking the process during which a heated solid material cools down. It has been used in the optimization of difficult problems such as machine scheduling, inventory control and vehicle routing problems in the literature [32]–[35]. One of the most important features of the SA algorithm is that it ensures the results that degrade the value of the objective function are included in the solution process under certain conditions in order not to be stuck at a local optimum. In other words, an improved objective function value (better than the current best solution) is always accepted, whereas non-improved solutions are accepted based on a probability value [34]. This mechanism is elaborated in the next section.

In basic SA algorithm, the criteria used to accept a worse objective function are the random numbers between 0 and 1, the improvement in the objective function, and the current temperature values. In the operation steps of the algorithm, as the temperature of the system decreases, the possibility of accepting worse results decreases because, as can be seen in (21), the decrease in \mathcal{T} value also decreases the selection probability of worse solutions. Thus, while the diversification feature is high at the beginning of the algorithm, intensification feature becomes prominent towards the last iterations. In other words, the algorithm performs a wider search by taking into account the worse solutions in the initial stage. However, it focuses on specific regions in the search space in the final stages. The probability of increase at temperature,

\mathcal{T} (in Kelvin), of δE amplitude in energy is presented in (20), where K is Boltzman constant:

$$p(\delta, \mathcal{T}) = \exp\left(-\frac{\delta E}{K\mathcal{T}}\right). \quad (20)$$

Therefore, the starting temperature of the system is a hyper-parameter of the algorithm and has a significant impact on the overall performance, such that it must be high enough to allow any feasible solution to be accepted. However, if it is set too high, the search process will be random until the temperature decreases to a certain level. As such, a certain \mathcal{T} value is determined as a stopping criterion in order not to prolong the search process excessively.

B. SA ALGORITHM FOR CELL SWITCHING AND SPECTRUM LEASING

To control the switching off/on of SBSs, it is necessary to determine the parameters of the algorithm in the first place. Then the objective function value of randomly generated initial solution s is calculated with (13). In this way, the revenues are obtained according to the energy saved from turning off some SBSs in the PN (7) and spectrum leased to the SN (9). During the search process, the algorithm attempts to transform the current solution s into one of its randomly selected new solution s' . However, in the developed algorithm, instead of randomly selecting a neighborhood structure, each neighborhood is applied in an order as in sequential variable neighborhood search (VNS) algorithm [36]. We also expanded the search area in each iteration due to the small number of neighborhood types.

Note that only feasible solutions which guarantee (14) and (15) are considered in the proposed SA algorithm. To ensure this, a feasibility check is performed first in each of the neighborhood solution produced. With the applied neighborhood structure, several temporal solutions can be produced until a feasible solution is obtained. If the revenue of the obtained solution with the new neighborhood structure, s' , is higher than the current solution s , the new solution is unconditionally accepted. If the revenue of the neighborhood solution is less than the existing solution, the probability of accepting the neighborhood solution is calculated as:

$$p = \exp\left(-\frac{R_T(s') - R_T(s)}{\mathcal{T}}\right). \quad (21)$$

After the local search process (after k iteration), the temperature is decreased according to the formula $\mathcal{T} = \mathcal{T} - \alpha$, where α is the temperature reduction parameter. The pseudo code for the developed SA based cell switching and spectrum leasing framework is presented in Algorithm 1.

The step-by-step implementation procedure of the proposed SA based cell switching and spectrum leasing framework is discussed in the following:

1) FEASIBILITY CHECK

In order for a solution to be evaluated within the algorithm, a preliminary check is performed to determine whether it is

feasible or not. For this reason, the transferred traffic loads of SBSs that are switched off in the s solution should not exceed the normalized capacity of the MBS (15). The pseudo code for feasibility check is shown in Algorithm 2.

Algorithm 1: SA Algorithm for Cell Switching and Spectrum Leasing

```

1 Randomly generate an initial solution:  $s_0 \in S$ 
2 while  $s_0$  is infeasible; do Randomly generate an initial solution:
    $s_0 \in S$ ;
3 Calculate revenue of  $s_0$ 
4 Define an initial temperature  $\mathcal{T} > 0$ 
5 Define temperature reduction function and  $\alpha$  value
    $s = s_0, s^* = s_0, f(s) = f(s_0), f(s^*) = f(s_0)$ ;
6 Define local search iteration number for each temperature ( $k$ )
7 while  $\mathcal{T} > 0.01$  do
8    $n = k$ ;
9   while ( $n > 0$ ) do
10    generate (1-reserve) neighbor solution  $s'$ 
11    while ( $s'$  is infeasible) do
12      generate (1-reserve) neighbor solution  $s'$ 
13       $\Delta = f(s') - f(s)$ ;
14      if ( $\Delta \leq 0$ ) then  $s = s'$ ;
15      else
16        generate a random number from uniform
17        distribution in the 0-1 range ( $u$ )
18        if ( $u < \exp(-\frac{\Delta}{\mathcal{T}})$ ); then  $s = s'$ ;
19        if ( $f(s') < f(s^*)$ ); then  $s^* = s'$ ;
20    end
21    generate (2-reserve) neighbor solution  $s'$ 
22    while ( $s'$  is infeasible) do
23      generate (2-reserve) neighbor solution  $s'$ 
24       $\Delta = f(s') - f(s)$ ;
25      if  $\tau^{i,1} \leq 1$  then  $s = s'$ ;
26      else
27        generate a random number from uniform
28        distribution in the 0-1 range ( $u$ )
29        if ( $u < \exp(-\frac{\Delta}{\mathcal{T}})$ ); then  $s = s'$ ;
30        if ( $f(s') < f(s^*)$ ); then  $s^* = s'$ ;
31    end
32    generate (swap) neighbor solution  $s'$ 
33    while ( $s'$  is infeasible) do
34      generate (swap) neighbor solution  $s'$ 
35       $\Delta = f(s') - f(s)$ ;
36      if ( $\Delta \leq 0$ ); then  $s = s'$ ;
37      else
38        generate a random number from uniform
39        distribution in the 0-1 range ( $u$ ) if
40        ( $u < \exp(-\frac{\Delta}{\mathcal{T}})$ ); then  $s = s'$ ;
41        if ( $f(s') < f(s^*)$ ); then  $s^* = s'$ ;
42    end
43     $n = n - 1$ ;
44  end
45   $\mathcal{T} = \mathcal{T} - \alpha$ 
46  apply (shaking) procedures to  $s^*, s = s^*$ 
47 end
48  $s^*$  is the heuristic solution of the problem

```

2) SOLUTION REPRESENTATION

The proposed SA algorithm has a representation scheme specially designed for the cell switching and spectrum leasing problem. It has a binary representation depending on whether the SBSs are off or on.

Algorithm 2: Feasibility Check

```

1 MBS traffic load =  $\tau^{i,1}$ ;
2 for  $i$  in  $s'$  do
3   if ( $s'(i) = 0$ ) then
4     calculate the transferred traffic load  $\sum_{j=2} \tau^{i,j}(1 - \Gamma_i^{i,j})$ ;
5      $\hat{\tau}^{i,1} = \tau^{i,1} + \sum_{j=2} \tau^{i,j}(1 - \Gamma_i^{i,j})$ ;
6     if  $\hat{\tau}^{i,1} \leq 1$  then
7        $s'$  is feasible
8     else
9        $s'$  is not feasible
10    end
11  end
12 end

```

3) INITIAL SOLUTION

In the SA algorithm, the initial solution, which is the first feasible solution at the beginning of the iterations in the SA algorithm, is generated randomly or with certain methodical approaches such as nearest neighbor heuristics [35]. Simple heuristic methods are considered to decrease the solution time and increase the quality of the solution in some NP-hard problems. However, in this work, the initial solution is generated randomly, and not with any constructive heuristic method because the optimized initial solution can be trapped in a particular local optimum within the search space.

4) NEIGHBORHOOD STRUCTURES

The proposed SA algorithm has three different neighborhood structures, seeking for better results from different aspects in each iteration. The SA algorithm also has nested iterations. The primary iteration is associated with temperature drop. Each temperature level represents one iteration and performs a global search in the search space. In addition, there are local search iterations in which neighborhood structures are applied sequentially at each temperature level. Neighborhood structures are named as **1-reserve**, **2-reserve** and **swap**, and they are frequently used in applications such as vehicle routing problems, travelling salesman problems (TSP), and location problems [32], [33]. In the neighborhood of 1-reserve, a random cell is chosen from the solution state s and the selected cell's index is denoted by j . If the value of $s(j)$ is 1, this value is changed to 0 and vice versa for the case where the value of $s(j)$ is 0. In the 2-reserve neighborhood, this process is performed for two different cells, while in the swap neighborhood, the values of two randomly selected cells are replaced with each other.

In addition to the neighborhood structures, the shaking tool is also used for diversification before each temperature change in the algorithm. After the local search procedure at certain temperature, the bit representation (i.e., 0 and 1 values) are changed randomly to search in different spaces. This action is to prevent the algorithm from being stuck at a local optimum. The demonstration of the implementation of neighborhood structures is shown in the Fig. 3.

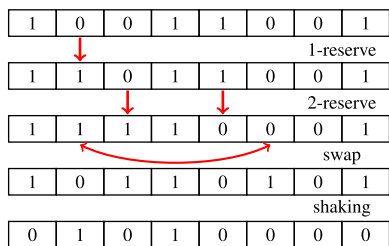


FIGURE 3. Illustration of the different types of neighborhood structures. The topmost bar shows the initial status of the SBSs, followed by the implementation of the three neighbourhood structures while the last bar represents the shaking operation.

5) PARAMETER SETTINGS

SA algorithm begins with five parameters: \mathcal{T} , \mathcal{T}_F , k , α and K . \mathcal{T} and \mathcal{T}_F are the initial and final temperatures, respectively. The initial temperature must be high enough to allow the acceptance of any feasible solution. If the initial temperature is too high, the probability of generating random solutions among feasible solutions at the beginning of the algorithm is higher. On the other hand, if the initial temperature is too low, the probability of getting stuck at the local optimum of the algorithm increases. The final temperature of the algorithm is set to avoid spending too much time in reaching the optimum. k is defined as the number of iterations of the local search procedure at each temperature, while α is the temperature reduction parameter. It refers to the amount by which the temperature will be decayed at the end of each iteration. K is Boltzmann constant and is used in calculating the probability of accepting or rejecting worse solutions. If the new objective function value is worse than current best solution, it will generate u , which is a random variable between 0 and 1. Then, the obtained solution will be accepted if the criterion represented in (21) is satisfied. Except for this situation, an improved objective function value is always accepted. We considered different SA algorithm design parameters that are frequently used in the literature [32], [33] and chose the ones that lead to the best results during the preliminary tests. The best SA parameter combination is $\mathcal{T} = 1$, $\alpha = 0.01$, $\mathcal{T}_F = 0.01$, $k = 10N$, where N indicates the total number of SBSs in the PN.

6) COMPLEXITY COMPARISON BETWEEN SA AND ES

An ES algorithm would perform a complete space search of all the possible configurations until the optimum configuration is found. This may be suitable for functions of few variables, but considering the cell switching and spectrum leasing problem, it would result in exponential computational complexity of $\mathcal{O}(2^N)$. Due to the computational complexity of problems like this and other NP-hard problems, many optimization heuristics have been developed in order to obtain optimal or approximate optimal solutions. In addition, the solution times of heuristic approaches are incomparably low compared to algorithms that try all possible scenarios. Because, not all feasible solution combinations

are considered in heuristic approaches. Heuristic approaches work with the best solution-oriented search and they focus on specific regions in the search space. Therefore, the computational cost of heuristic approaches are very low compared to ES, especially in large-scale cell switching problems. One widely used technique is the SA algorithm, by which we introduce a degree of stochasticity, potentially shifting from an optimal to a sub-optimal solution, in an attempt to reduce the complexity, escape local minima, and converge to a value closer to the global optimum.

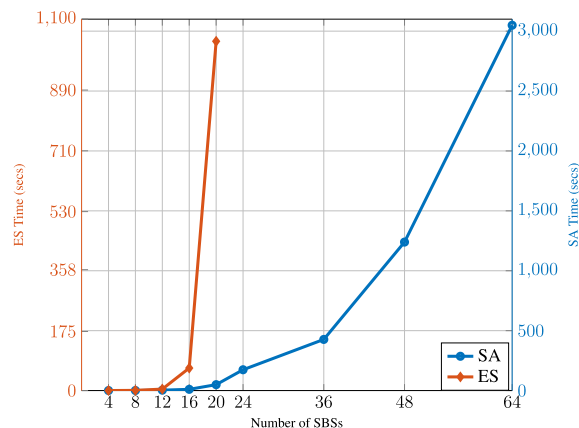


FIGURE 4. Time complexity comparison between ES and SA.

However, the time complexity of heuristic algorithms such as the SA algorithm cannot be easily determined because such algorithms do not guarantee to find the global optimal solution within a certain time limit. Instead, determining the total simulation run time of the algorithm can give us an idea of the computational complexity of the algorithm. Fig. 4 shows the simulation run time comparison between ES and the proposed SA algorithm. It can be clearly seen that the simulation run time of the ES algorithm is very small when the number of SBSs are less than 16. However, we notice a huge leap in simulation time when the number of SBSs is increased from 16 to 20 because the number of search spaces of the ES increases exponentially with the number of SBSs. This accounts for the very wide difference in the simulation time that is observed when the number of SBSs are increased to 20 compared to when they were 16. It should be noted that we stopped the simulation at 20 SBSs for the ES algorithm because of the limitation of our computer as it would take days to complete the simulation when the number of SBSs are increased to 24. The simulation time of the SA algorithm is also very low until about 20 SBS when it starts to increase with higher magnitudes. But this is much lesser than the magnitude of simulation time increase that is observed with the ES algorithm. The SA algorithm exhibits a polynomial order of computation complexity because it does not have to consider all the search spaces like the ES algorithm in order to determine the optimal cell switching and spectrum leasing strategy.

ES algorithm searches all the neighborhood solutions regardless of whether a solution vector yields worse results in terms of the objective function. This situation causes an unnecessary computational cost increase in the algorithm. However, SA does not check every solution in the entire solution space. While doing a local search in a solution space, it looks at the solution regions adjacent to the best solution. This is because the global optimum is likely to be close to the local best solutions. As a result, SA's superiority over ES algorithm in terms of computational complexity is due to its solution search strategy. Hence, the ES algorithm is only suitable for small networks with few SBSs while the SA algorithm can be applied even when number of SBSs are very many.

VI. PERFORMANCE EVALUATION

The proposed cell switching and spectrum leasing framework can be implemented in any network regardless of the network size in terms of the number of MBSs involved. Since the framework is implemented independently at each MBS, which is responsible for controlling all the SBSs under its coverage, the simulations are conducted for a single MBS with multiple SBSs for the sake of brevity. Hence, we need to develop one framework and implement it in all the other MBS-SBSs configuration throughout the network. The system configuration comprises the hardware, which is a HP-TXH0CCYBD0HV desktop computer and has the following specifications: The processor is Intel core i7-8700 @3.2 GHz, RAM of 16 GB, with Windows 10 Enterprise operating system and 475 GB hard disk capacity. The software employed is the Spyder version 4.0.1 which runs Python version 3.7. The development environment that is utilized is Anaconda because it has a complete suite for Python development as well as that of other high-level languages. The PN, SN, and SA algorithm parameters used in the simulations are presented in Table 1.

TABLE 1. Simulation parameters.

Parameter	Value
Bandwidth of MBS (MHz)	20
Bandwidth of SBSs, SN-BSSs (MHz)	15, 10, 5, 3
Number of RBs per MBS	100
Number of RBs per SBSs, SN-BSSs	75, 50, 25, 15
P_{ix} (MBS, RRH, micro, pico, femto) (W)	20, 20, 6.3, 0.13, 0.05
P_{io} (MBS, RRH, micro, pico, femto) (W)	130, 84, 56, 6.8, 4.8
ζ (MBS, RRH, micro, pico, femto)	4.7, 2.8, 2.6, 4.0, 8.0
$P_{BS,S}^{i,j}$ (RRH, micro, pico, femto) (W)	56, 39, 4.3, 2.9
Initial temperature, \mathcal{T}	1
Final temperature, \mathcal{T}_F	0.01
Fixed spectrum price (per RB)	£0.13
Fixed electricity price (per kWhr)	£0.1293
Number of PN MBS, SBSs	1, 12
Number of SN BSs	12

A. DATA SET AND PRE-PROCESSING

To compute the total revenue of the HetNet using (12), the traffic demand of each BS in the PN (τ) and SN (Ψ) is required. We leveraged the call detail record (CDR) data

set of the city of Milan, Italy that was made available by Telecom Italia [37]. In the data set, Milan city was divided into 10,000 square grids with each having an area of 235×235 square meters. In addition, the call, short-message and Internet activities that were carried out in each grid was recorded every 10 minutes over a period of two months (November-December 2013). Although the activity levels contained in the data set are without unit and no additional information was provided regarding how the data set was processed, we decided to interpret the CDR of each grid as the traffic loads as they signify the amount of interaction between the users and the mobile network within the grid in each time slot. However, during the data processing stage of this work, we considered only the Internet activity level as the traffic load for the PN since it was the most significant part of the data set and also considering the fact that 5G networks would be mainly Internet based. The Internet activity level of two grids were selected at random to represent the traffic load of the MBS while that of one grid was chosen for each SBS. Then, the traffic loads were normalized separately according to the capacity of each type of SBS. We assume that the traffic demand of each BS in the SN is a fraction of the traffic demand of the SBSs in the PN such that $\Psi = \beta\tau$ where β is a variable between 0 and 1 (β was chosen to be 0.7 in this work). The traffic demand of the SN is shifted so that its maximum traffic demand coincides with the period of the day when the spectrum leasing price is minimum in order to depict the DT case while for the NDT case, the traffic demand remains intact.

B. BENCHMARKS

We compare the performance of the proposed method with three benchmark methods namely: ES, A-type, and D-type algorithms, which are briefly described in the following paragraphs.

1) EXHAUSTIVE SEARCH (ES)

This method sequentially considers all the possible cell switching and spectrum leasing combinations in order to determine the optimal off/on switching policy that would result in maximum revenue to the PN while ensuring that the QoS of the network is maintained. Therefore, this method is guaranteed to always find the optimal policy without violating the QoS of the network. However, the computational complexity involved in sequentially searching through all the possible combinations makes it unsuitable for online implementation. The goal of any other algorithm is to closely approximate the policy obtained from this approach, hence, it is suitable as a benchmark for this problem.

2) SORTING-BASED ALGORITHMS

Two additional benchmark algorithms are developed using the sorting approach which we have named A-type and D-type heuristic respectively. In the D-type heuristic, we first evaluate a utility function, \mathcal{N} , which is the difference between the traffic demand of the SN BSs and that of the PN BSs,

i.e., $\mathcal{N} = \Psi - \tau$. This utility function \mathcal{N} is important because we are not only interested in switching off the SBSs with low traffic demand, but also those whose associated SN BS has high spectrum demand. It is necessary to satisfy both conditions if the revenue of the PN is maximized because both of them affects the total revenue in (10) that can be generated by the PN. In addition, since the total revenue of the PN is dependent on the amount of revenue that can be obtained from energy savings and spectrum leasing, thus, higher values of \mathcal{N} would result in greater revenue generation due to higher contributions from both components. On the other hand, lower values of \mathcal{N} might result in lesser revenue generation due to smaller contribution either from the energy savings or spectrum leasing. After evaluating \mathcal{N} , the SBSs are arranged in descending order according to the value of \mathcal{N} . Then, the traffic load of the SBSs are sequential offloaded to the MBS until the capacity of the MBS is reached. The procedure for implementing A-type heuristic is similar to that of D-type except that in A-type, the SBSs are sorted in ascending order according to \mathcal{N} .

C. PERFORMANCE METRICS

The metrics that would be used in evaluating the performance of the proposed and benchmark methods are briefly discussed in this section.

1) TOTAL REVENUE

The goal of this work is to determine the maximum revenue that can be obtained by the PN over a given period of time, T . As described in Section IV, this is obtained by combining the revenue due to energy saving from cell switching and the revenue obtained from leasing the spectrum to the SN. The total revenue of the network can be obtained from (13).

2) AVERAGE NETWORK THROUGHPUT

The effect of the proposed framework on the QoS of the network is evaluated using the network throughput metric. Here, we consider the network throughput to be the traffic demand that can be served by all the remaining BSs (both MBS and active SBSs) after cell switching and spectrum leasing operation has been executed. To estimate this throughput, we assume that the activity level contained in the employed data set are throughput demands (in Mbps) so that τ can be seen as the normalized throughput of each BS (i.e., MBS and SBSs). Therefore, the average network throughput $Q_{\text{Net}}(t)$ can be obtained by aggregating the throughput demands of all active SBSs and the MBS [16], such that:

$$Q_{\text{Net}}(t) = Q_{i,1}(t) + \sum_{j=2} Q_{i,j}(t), \quad (22)$$

where $Q(t)$ is the average received throughput from each BS and can be expressed as:

$$Q(t) = r_m(t)U_m(t), \quad (23)$$

where r_m is the average throughput that is allocated to each user (assuming equal resource allocation) and U_m is the total number of users served by each BS at a given time t .

D. RESULTS AND DISCUSSIONS

Fig. 5a shows the hourly total revenue obtained by the PN following the fixed electricity and spectrum pricing policy with NDT spectrum demand using the proposed and benchmark methods. In addition, the traffic load of the PN MBS, $\tau^{i,1}$, is also presented. The first thing we observe from Fig. 5a is that the revenue obtained from all methods follows a trend that is opposite of that of the traffic demanded of the PN. This is so because during the periods of the day where the PN traffic is low, more SBSs can be switched off which translates to more revenue generation from energy savings and spectrum leasing. The opposite is the case when the traffic of the PN is high. Second, the SA algorithm follows ES almost exactly, since it is able to employ its mechanisms such as feasibility check and neighbourhood structures to determine the optimal cell switching and spectrum leasing pattern, but with much lesser complexity.

Third, both the A-Type and D-type heuristic solutions never outperform ES and SA algorithms because they also respect the constraint of not exceeding the MBS capacity. Even though they both respect the MBS capacity in order to maintain the QoS of the network, they utility, \mathcal{N} , used in determining which BSs to switch off only considers the difference in traffic demand between the PN and SN, but is not able to distinguish between the various types of BSs present. In this work, the PN and SN BSs have different capacities and power consumption, as a result, switching off a SBS with higher capacity and power consumption and leasing its spectrum to the SN would result in higher revenue than switching off one with a lower capacity. This limitation accounts for the lesser revenue obtained from both the A-type and D-type heuristics.

Another interesting point to discuss about the observations in Fig. 5a is that the D-type heuristic mostly outperforms the A-type heuristic because it switches off the SBS with highest utility, \mathcal{N} , values first and this helps in the generation of more revenue compared to A-type which does the opposite. However, this performance difference is mostly observable during the times of low traffic as there are more options and the higher utility is able to find a better solution. For the time when the network traffic is high, they start performing alike, since the number of cell switching and spectrum leasing options becomes very low. Overall, the performance difference between the D-type and A-type solutions is not large, as the former outperforms the latter with a minimum of 1% and a maximum of 29%. The last observation worth discussing is that the SA solution mainly outperforms both A-type and D-type solutions (by about 90% and 65% respectively) during periods of high traffic. The reason for this is that the number of cell switching and spectrum leasing options becomes very few during this period, thereby making it very difficult for them to find the best solution while the SA solution is carefully designed to be able to perform excellently well even in such periods.

This is because the SA algorithm can search in different regions of the solution space. This is due to the diversification

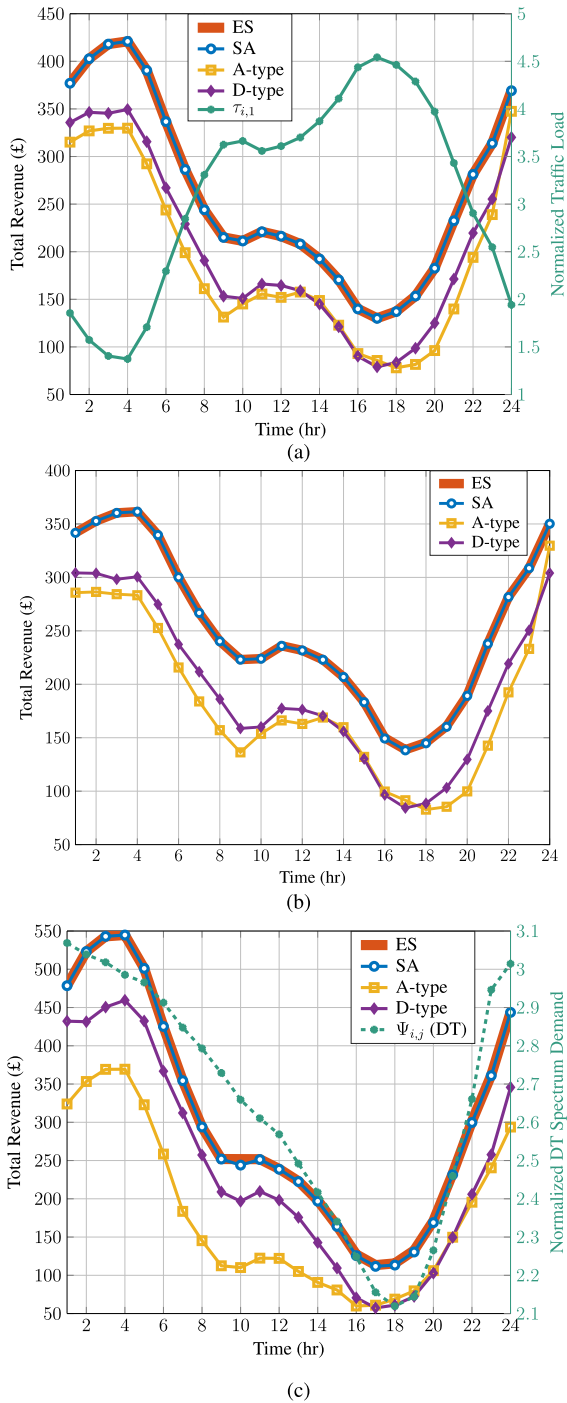


FIGURE 5. The revenue obtained by the PN due to cell switching and spectrum leasing from fixed pricing policy and dynamic pricing policy (DT and NDT spectrum demand) for 12 SBSs over a 24 hour period. (a) The left y-axis is the total revenue obtained from fixed pricing policy with NDT spectrum demand while the right y-axis is the traffic load of the PN MBS. (b) Total revenue from dynamic pricing policy with NDT spectrum demand. (c) The left y-axis is the total revenue from dynamic pricing policy with DT spectrum demand while the right y-axis is the traffic demand of the SN.

feature provided by the shaking procedure. SA performs a local search at each temperature level and arrives at the best solution (or approximate best) in a specified region of the solution space. Then the shaking procedure is applied with

temperature drop. Thus, in the next iterations, it compares the local best solutions in different regions of the solution space with the current best solution and searches up to the termination criterion. However, heuristic methods such as A-type and D-type operate fixed (usually one or more feature-dependent utility functions) rules. This causes heuristic methods to get caught in the local best solution trap. In addition, the SA algorithm includes different neighborhood search strategies. These strategies provide more flexibility in local search and for this they determine the probabilistic acceptance criteria according to the temperature level.

Fig. 5b presents the total revenue obtained every hour by the PN when the dynamic pricing policy with NDT spectrum demand is considered using the proposed and benchmark methods. In the dynamic pricing policy, the prices of both electricity and spectrum vary at different times of the day depending on the amount of spectrum or electricity demanded. Similar to what was observed in Fig. 5a, the pattern of the total revenue over the whole day is the inverse of the traffic profile of the PN. Moreover, the revenue is generally scaled down compared to Fig. 5a, and this is more noticeable during periods of low traffic. This is because a dynamic pricing policy is used, where the PN sometimes needs to lease the spectrum for less and at those times it also earns less from energy savings because the prices are lower. The D-type heuristic also slightly outperforms the A-type heuristics with almost the same percentage (1% to 29%) as in Fig. 5a, due to the fact that higher utility values are considered first during cell switching which helps in greater revenue generation in the former compared to the latter. The aforementioned confirms our previous argument on why the performance of the two benchmark algorithms are similar. The proposed SA algorithm also greatly outperforms the A-type and D-type algorithms with a similar percentage (90% and 65% respectively) as in Fig. 5a mostly during the period of high traffic in the PN because there are lesser cell switching and spectrum leasing options which make it difficult for the benchmark solutions to make the optimum decisions.

Another important point to note is that although the D-type solution offers better results than A-type, these two algorithms have similar working mechanisms as can be seen in Fig. 5a and Fig. 5b. The D-type sorts the SBSs in descending order of the value of the utility, \mathcal{N} , in order to determine the SBSs to turn off and lease their spectrum to the secondary network while the D-type type does the opposite. Heuristic approaches such as A-Type and D-Type do not guarantee an optimal solution. However, the solutions found by such algorithms may converge to the optimal or approximate optimal. Heuristic algorithms have a probability of being optimal if the local search region is close to the global optimum in the solution space. This is also the case at the 24th hour. The results of the numerical experiments demonstrate that the proposed A-type and D-type benchmark methods obtain near optimal solutions at the 24th hour. Another reason for this may be that there are not many feasible solution alternatives

in the solution space at this period. In Fig. 5a, at the 24th hour, the results of the D-type, A-type, SA and ES algorithms are £320, £347, £369 and £369, respectively. Similarly, in Fig. 5b, the revenue values of £304, £329, £350 and £350 are obtained with D-type, A-type, SA and ES algorithms, respectively. However, it should be noted that benchmark methods still could not obtain the optimal solution. In cases where the problem size is small, it is natural for heuristic algorithms to reach optimal results. On the other hand, the larger the problem size, the less likely it is for them to converge to the optimal solution.

Fig. 5c presents the total revenue obtained by the PN when dynamic pricing policy with DT spectrum demand is considered. In this case, the SN decides to delay its data transmission to periods when the spectrum price is low (which also coincides with period of low traffic demand in the PN) so that they can access more spectrum at a cheaper rate. It can be observed that there is an overall increase in the total revenue obtained by the PN in Fig. 5c, compared to Fig. 5a and Fig. 5b: the total revenue obtained from the proposed SA framework is about 19% and 16% higher than that obtained in the Fig. 5a and Fig. 5b, also it is evidenced by the peak value of the revenue of Fig. 5c being about £183 and £123 higher than that in Fig. 5a and Fig. 5b respectively. This is because in dynamic pricing policy with DT spectrum demand, the SN can lease more spectrum as the periods of low traffic in the PN matches the period of high spectrum demand by the SN although the prices are lower. This statement is validated by comparing the traffic demand of the PN in Fig. 5a with the DT spectrum demand in Fig. 5c; i.e., periods of lowest traffic demand in the PN (e.g., in the first quarter of the day where the traffic load is 14%) coincides with periods of highest spectrum demand from the SN (about 28%) so that even though the spectrum prices are lower at these times as seen in Fig. 2, the large amount of spectrum demanded by the SN causes the total revenue in this scenario to be highest.

The performance difference between the D-type and A-type heuristics is more significant in the dynamic pricing policy with DT spectrum demand scenario compared to both the fixed and dynamic pricing policy with NDT scenarios in Fig. 5a and Fig. 5b with values ranging from 5.3% to 86%. The reason for the wider performance gap is that the NDT spectrum demand is responsible for preventing the D-type heuristic from significantly outperforming A-type heuristic. This phenomenon originates from the fact that in the fixed and dynamic pricing policy with NDT spectrum demand, the trend of the SN traffic demand follows the PN traffic demand, hence the margin in the values of \mathcal{N} is smaller in the both cases compared to the dynamic pricing policy with DT spectrum demand, thus accounting for the lesser total revenue results of A-type and D-type heuristics in the previous scenarios. On the other hand, for the dynamic pricing policy with DT spectrum demand (Fig. 5c), since the traffic demand of the SN is the inverse of the traffic load of the PN, the difference in the values of \mathcal{N} at different time slots is higher and since D-type gives preference to SBSs with higher \mathcal{N}

during cell switching and spectrum leasing, more revenue is generated by the D-type compared to A-type, hence the reason for the wider margin in the revenue generated in the former compared to the latter. In addition, the SA algorithm greatly outperforms the A-type and D-type benchmarks in terms of revenue generation by a maximum of 124% and 95% respectively, during periods of high traffic demand in the PN. These values are 34% and 31% higher than its performance against the two benchmarks in both the fixed and dynamic pricing with NDT spectrum demand in Fig. 5a and Fig. 5b respectively. The reason is that the SA algorithm is able to take advantage of the available options to switch off SBSs during period of high traffic which coincides with low spectrum demand by the SN in order to generate much higher revenue than the A-type and D-type algorithms.

It can also be observed that the results of D-type and A-type methods are almost the same in a few instances with the A-type even slightly surpassing that of the D-type at some points. For the NDT cases (with both fixed and dynamic pricing policies), Fig. 5a and Fig. 5b, this occurs when both the data traffic of the PN and the spectrum demand of the SN are high. This is due to the fact that the difference in the values of the utility in this period is very small, thus, there is very little revenue from spectrum leasing as the SN is not able to access spectrum due to lack of dormant spectrum from the PN. Also, very little revenue can be obtained from energy saving since only very few SBSs can be turned off due to very high traffic load in the PN.

For the DT case with dynamic pricing policy, Fig. 5c, the similarity in the results of both the D-type and A-type heuristics occurs at 16hr-21hr, when the traffic demand of the PN is very high and the spectrum demand of the SN is very low. At these periods, both benchmarks begin to function alike because even though there is a large difference in the value of the utility function, there is very little opportunity to switch off the SBSs due to high traffic in the PN. Hence, there is an insignificant difference in the performance of both benchmarks as relatively less revenue can be obtained during this period. The traffic load of the PN is also high from the 8th to 10th hour, even though it is not as high as that of 16th to 21st hour. However, the spectrum demand of the SN is quite high from the 8th to 10th hour but very low from the 16th to 21st hour. As a result, the D-type solution clearly outperforms the A-type solution from the 8th to 10th hour because it switches off SBSs with the highest utility first, which makes it able to take advantage of the available spectrum (due to not so high traffic in the PN) to generate higher revenue than the A-type solution which switches off the SBSs with lowest utility first.

Fig. 6a shows the total amount spent by the SN for spectrum purchase as well as the total quantity of spectrum obtained for a 24 hours period using the proposed SA-based framework and ES while Fig. 6b shows the unit cost of the spectrum (i.e., price per RB) for both DT and NDT spectrum demand using both algorithms. From Fig. 6a we can see that the total amount expended by the SN on spectrum purchase as

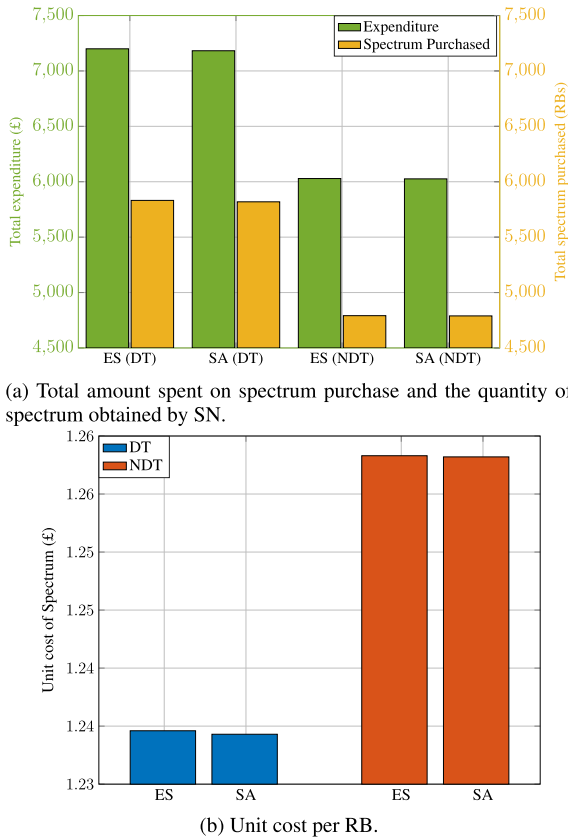


FIGURE 6. Total expenditure and quantity of spectrum purchased by SN and the average unit cost of the spectrum for 12 SBSs.

well as the quantity of spectrum purchased are significantly higher in DT than in the NDT scenario with a percentage difference of 19% and 21% respectively. The rationale behind this is that most of the periods when the electricity and spectrum prices are low are also the periods when the traffic loads of the MBS and SBSs are low. As such, more SBSs can be turned off in order to ensure that more spectrum is available for SN to purchase during these periods. Although more spectrum is available to the SN for both DT and NDT spectrum leasing scenarios with the dynamic pricing policies during periods of low traffic load in the PN, the difference in the volume of spectrum demanded in both cases is what accounts for the difference in the amount expended on spectrum purchase in Fig. 6a.

In the DT case, the data to be transmitted is delayed until when the spectrum and electricity prices are low, which means that the SN is able to take advantage of more spectrum available in order to offer more data services to its users. However, for the NDT case, even though more spectrum is available during periods of low prices, the spectrum demanded by the SN during this period is also low, so lesser revenue is generated and fewer data services can be offered in this scenario. For example, in the first quarter of the day where the traffic load of the PN is the lowest (about 14%), the revenue generated by the dynamic pricing policy with DT spectrum

demand is 47% higher than that obtained from the dynamic spectrum demand with NDT spectrum demand because more spectrum is available for leasing as well as a corresponding high spectrum demand from the SN. However, the availability of more spectrum does not correspond with high spectrum demand in the NDT case thereby leading to a lesser revenue generation. Fig. 6a also reveals that the total expenditure and quantity of spectrum purchased using SA algorithm is almost the same as that of ES algorithm which validates the excellent performance of the SA algorithm earlier discussed under Fig. 5a, Fig. 5b and Fig. 5c.

The purchase of more spectrum by the SN in the DT case compared to the NDT case means that the SN incurs more expenses during DT data transmission compared to NDT data transmission. Therefore, the DT case is more beneficial to the PN because it results in more total revenue. It is also beneficial to the SN because it pays less for a unit of spectrum even though its total expenditures increase. Hence, where possible (for suitable applications), we can conclude that the shift in the SN traffic demand would be recommended. However, the kind of shift in the data transmission time of the SN does not have to be implemented in exactly the same way as in this work, instead, depending on the type of application, the latency requirements are evaluated and the appropriate shifts in the traffic is implemented accordingly, making the DT spectrum demand quite flexible and dynamic. Although this traffic shift may not always coincide with the cheapest time but to a cheaper time. In summary, DT spectrum demand will make the business of both PNs and SNs more sustainable because it is more profitable for both parties.

A major constraint in this work is to ensure that the QoS of the network is maintained by ensuring that traffic served by the network remains constant even when some SBSs are switched off. The PN is supposed to respect the capacity constraints of the MBS before switching off any SBS. From the simulations, we observed that both the proposed and benchmark solutions are able to maintain the QoS of the PN. The SA algorithm uses the feasibility check in Algorithm 2 to ensure that only solutions that do not exceed the capacity of the MBS are considered. The ES algorithm follows similar procedure by guaranteeing that solutions that exceed the MBS capacity are excluded when selecting the optimal cell switching and spectrum leasing strategy. Both the A-type and D-type algorithms are implemented in such a way that the traffic load of the SBSs are offloaded sequentially (in ascending and descending order respectively) and once the offloading capacity of the MBS is attained, no further SBS is turned off. By so doing, they both guarantee that the throughput of the network is maintained. It is also worthy of note that irrespective of the pricing model used for electricity and spectrum (fixed or dynamic) and the type of spectrum demanded by the SN (DT or NDT), the average throughput of the PN remains the same. This is because both the proposed and benchmark algorithms take the traffic-QoS constraint (14) into consideration thereby ensuring that the QoS of the network is not violated.

In this study, SA, which is one of the meta-heuristic algorithms, is applied to solve the cell switching and spectrum leasing problem. Meta-heuristic algorithms such as SA may differ from each other in terms of various prominent features. In other words, these methods have various advantages and disadvantages. Although the SA algorithm is one of the most important meta-heuristic algorithms, it is insufficient when compared to modern meta-heuristic algorithms in terms of some features such as convergence speed and parallel computation. Thus, the SA algorithm can be hybridized with different meta-heuristics in order to perform parallel computation. In addition, the SA algorithm is a no memory class algorithm that offers a single solution. Memory-based meta-heuristic algorithms such as genetic algorithm, particle swarm optimization can be applied to the current problem to present a comparative performance test study. As another option, an adaptive algorithmic structure can be presented to improve the performance of the SA algorithm.

VII. CONCLUSION

In this paper, we considered the problem of revenue maximization through cell switching and spectrum leasing in order to maximize the revenue of the PN, which comprises a HetNet with different types of SBSs while the SN comprises SN BSs. An SA algorithm based solution was proposed to determine the optimal cell switching and spectrum leasing strategy that would result in maximum revenue for the PN while ensuring that the QoS of the network is maintained. We considered fixed and dynamic pricing policy for both electricity and spectrum. Under the dynamic pricing policy, both DT and NDT spectrum demand scenarios were considered in order to determine the effect of these policies on the revenue of the PN as well as the expenditure and amount of service demands that can be met by the SN. The simulation results show that the PN is able to obtain more revenue using the dynamic pricing policy with DT spectrum demand. Moreover, in the DT spectrum demand scenario, the SN is able to lease more spectrum when the spectrum prices are low, which enables it to serve more data services at a reduced average unit price. Thus, making this scenario more profitable to the SN compared to the fixed or dynamic pricing policy with NDT spectrum demand scenarios. Overall, the performance of the proposed method is almost the same as that of the ES algorithm with lesser time complexity.

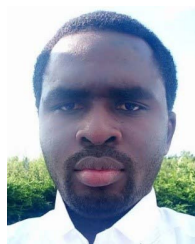
This study has some limitations. First, we assumed that there is only one secondary network (SN) base station (BS) under the coverage of each primary network (PN) BS; however, in reality, there could be multiple SN BSs trying to lease the spectrum simultaneously. Furthermore, the current work assumes a terrestrial type cellular network only, but the unmanned aerial vehicle (UAV) mounted BSs (UAV BSs) have been quite popular, and their integration to the current problem was not considered in this study. In this regard, in future, we intend to investigate the scenario where more than one SN BSs are competing to lease the spectrum of each PN BSs. In this case, the optimization problem becomes more

complex as the PN would have to decide which of the SN BSs to lease the available spectrum including the possibility of leasing the spectrum to more than one SN BSs at the same time. The solution to this problem would require the extension of the current cell switching and spectrum leasing framework to include sharing of the available spectrum and matching it with the required number of SN BSs. This would also require the development of an additional model for spectrum sharing using matching algorithms. We also intend to employ UAV mounted BSs (UAV BSs) to provide additional offloading capacity for the PN BSs, so that the spectrum of PN BSs can be evacuated for SN BSs, to enable delay and rate sensitive users transmit their data during periods of high traffic demand in the PN.

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