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Copyright HolderName	The Author(s), under exclusive license to Springer Nature Switzerland AG		
Corresponding Author	Family Name	Noma-Osaghae	
	Particle		
	Given Name	Etinosa	
	Prefix		
	Suffix		
	Role		
	Division		
	Organization	Covenant University	
	Address	Ota, Ogun State, Nigeria	
	Email	etinosa.noma-osaghae@covenantuniversity.edu.ng	
Author	Family Name	John	
	Particle		
	Given Name	Samuel N.	
	Prefix		
	Suffix		
	Role		
	Division		
	Organization	Nigeria Defence Academy	
	Address	Kaduna, Kaduna State, Nigeria	
	Email	samuel.john@nda.edu.ng	
Author	Family Name	Aragha	
	Particle		
	Given Name	A. I.	
	Prefix		
	Suffix		
	Role		
	Division		
	Organization	Nigeria Defence Academy	
	Address	Kaduna, Kaduna State, Nigeria	
	Email	araga9393@gmail.com	
Author	Family Name	Okokpujie	
	Particle		
	Given Name	Kennedy	
	Prefix		
	Suffix		

	Role		
	Division		
	Organization	Covenant University	
	Address	Ota, Ogun State, Nigeria	
	Email	kennedy.okokpujie@covenantuniversity.edu.ng	
Abstract	Small base stations (SB networks. However, car via SBS deployment do overall efficiency. The u consumption. This resea algorithm to find the der network. A stochastic ge strategies are also explo favours lower densities traffic levels. The strateg than the random sleep r solution to the SE and E algorithm generated all ParetoSearch algorithm study provides cellular r achieve the desired through	Small base stations (SBSs) play a vital role in 5G communication to improve the throughput of cellular networks. However, care needs to be taken to ensure that improving the throughput of a cellular network via SBS deployment does not lead to unacceptable interferences that negatively impact the network's overall efficiency. The unpredictable nature of SBS deployment also has implications for energy consumption. This research study proposes a weighted-sum modified particle swarm optimization (PSO) algorithm to find the density of SBSs that maximizes the throughput and energy gains of a cellular network. A stochastic geometry approach is taken to the optimization process, and some form of SBS sleep strategies are also explored at high and low traffic levels. The study showed that the strategic sleep mode favours lower densities of SBSs at lower transmission power levels than the random sleep mode at low traffic levels. The strategic sleep mode selects higher densities of SBSs at higher transmission power levels than the random sleep mode at high traffic levels. The strategic sleep mode provided a better optimal solution to the SE and EE maximization problem at both high and low traffic level. In contrast, the ParetoSearch algorithm could generate the Pareto optimal front at only low traffic levels. The result of this study provides cellular network engineers with a means of simultaneously adjusting network parameters to	
Keywords (separated by '-')	Heterogeneous cellular Macrocell - Small cell -	networks - Stochastic geometry - Particle swarm optimization - Small base station - Throughput - User equipment	



### Optimizing Stochastic Small Base Station Deployment with Particle Swarm Technique

Etinosa Noma-Osaghae<sup> $1(\boxtimes)$ </sup>, Samuel N. John<sup>2</sup>, A. I. Aragha<sup>2</sup>, and Kennedy Okokpujie<sup>1</sup>

<sup>1</sup> Covenant University, Ota, Ogun State, Nigeria {etinosa.noma-osaghae, kennedy.okokpujie}@covenantuniversity.edu.ng <sup>2</sup> Nigeria Defence Academy, Kaduna, Kaduna State, Nigeria samuel.john@nda.edu.ng

Abstract. Small base stations (SBSs) play a vital role in 5G communication to improve the throughput of cellular networks. However, care needs to be taken to ensure that improving the throughput of a cellular network via SBS deployment does not lead to unacceptable interferences that negatively impact the network's overall efficiency. The unpredictable nature of SBS deployment also has implications for energy consumption. This research study proposes a weightedsum modified particle swarm optimization (PSO) algorithm to find the density of SBSs that maximizes the throughput and energy gains of a cellular network. A stochastic geometry approach is taken to the optimization process, and some form of SBS sleep strategies are also explored at high and low traffic levels. The study showed that the strategic sleep mode favours lower densities of SBSs at lower transmission power levels than the random sleep mode at low traffic levels. The strategic sleep mode selects higher densities of SBSs at higher transmission power levels than the random sleep mode at high traffic levels. The strategic sleep mode provided a better optimal solution to the SE and EE maximization problem at both high and low transmit levels. The proposed PSO algorithm generated all Pareto optimal fronts regardless of the network traffic level. In contrast, the ParetoSearch algorithm could generate the Pareto optimal front at only low traffic levels. The result of this study provides cellular network engineers with a means of simultaneously adjusting network parameters to achieve the desired throughput and energy savings in SBS-enhanced cellular networks.

Keywords: Heterogeneous cellular networks  $\cdot$  Stochastic geometry  $\cdot$  Particle swarm optimization  $\cdot$  Small base station  $\cdot$  Macrocell  $\cdot$  Small cell  $\cdot$  Throughput  $\cdot$  User equipment

### 1 Introduction

The proliferation of new network services and the ever-increasing number of mobile devices has prompted the need for innovative ways to meet the resulting geometrical increase in traffic [1]. Small base stations (SBSs) are used to improve the throughput of a cellular network [2]. The increased levels of data traffic may be served by the

uncoordinated deployment of SBSs to traffic hotspots within the area of already existing macro cells [3]. The use of SBSs provides the possibility of managing energy consumption with the help of the correct type of sleep-mode technique without any decline in the Signal-to-Interference-Plus-Noise Ratio (SINR) of the cellular network [4].

A load profile is used in the energy industry to manage power generation, transmission, distribution, and utilization. The same concept can be applied in cellular communication to manage uncoordinated SBS deployment in a way that uses energy optimally [5]. The use of temporal and spatial variations in data traffic levels to selectively put SBSs to sleep offers a potent means for network operators to deploy SBSs to achieve throughput and energy consumption goals [6]. SBSs provide a feasible means of increasing network throughput, but with the probability of causing unintended deterioration of the cellular network's Quality of Service (QoS) and unmanageable network operation expenses due to increasing energy consumption costs.

This research study proposes particle swarm optimization to arrive at the required density and transmit power of the SBSs that serves the network connectivity needs of every UE in a cellular network without any drop in QoS and at network operator managed energy consumption costs. A two-tier traffic-aware heterogeneous cellular network (HCN) is modelled using stochastic geometry, and the closed-form of its energy-spectral-efficiency is derived. A multiobjective optimization problem to simultaneously maximize the spectrum and energy efficiency of the two-tier HCN is formulated and solved using particle swarm optimization. The proposed PSO-based algorithm is then compared with the ParetoSearch algorithm in MATLAB2018b for random sleep mode at low traffic levels.

The remaining part of the paper is organized thus; Section 2 summarises the existing literature on SBSs deployment optimization, and Sect. 3 details the study's methodology. In Sect. 4, the results of the simulations are presented and discussed. The paper is then concluded, and a reference section is provided.

#### 2 Literature Review

Multiobjective optimization problems (MOP) are formulated to study the tradeoff between throughput and energy consumed in heterogeneous cellular networks (HCNs). In developing a MOP, the goal is to eventually change the MOP into a Single-objective Optimization problem (SOP) that can be solved quickly. In sample research, a MOP was formulated to study the tradeoff between energy efficiency (EE) and spectral efficiency (SE) in an HCN [7]. Transmit power limitations and minimum rate requirements were used as constraints. The MOP was changed into an SOP through weights that telecommunication service providers can tune to achieve the desired SE and EE tradeoff. Future cellular networks thrive on fine-tuned spectral and energyefficient systems.

A shared spectrum scenario was used to analyze the SE-EE tradeoff in a two-tier heterogeneous cellular network. The result of the simulations showed that improvement in SE using overlaid small base stations (femtocells) is strongly dependent on load level and the power consumption pattern of the serving base station. A multiobjective optimization problem was formulated to solve the SE-EE tradeoff challenge. The

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multiobjective optimization problem was solved to yield the Pareto optimal tradeoff points between SE and EE. Quality of Service (QoS) was taken as the constraint of the optimization problem. The SE-EE tradeoff was quantified as a Lebesgue measure [8]. Multiobjective optimization was used to analyze the tradeoff between spectrum and energy efficiency in a heterogeneous cellular network focusing on the system's deviceto-device communication. The key parameters were resource allocation for spectral efficiency and power allocation for energy efficiency. The interference in the network was considered a constraint. The  $\varepsilon$ -constraint method was used to solve the multiobjective optimization problem that maximizes the EE and SE without any minimum rate decline for device-to-device and cellular users [9]. The result was a two-stage iterative algorithm that converges quickly to the Pareto-optimal solution.

A firefly inspired algorithm examined the relationship between area spectral efficiency and energy efficiency in HCNs [10]. In the sleep/active mode of HCN operation, the resource management problem was solved using a deactivation algorithm. A study investigated using a deactivation algorithm to manage resources within an HCN. The findings showed that spectral efficiency decreased whenever there was a limit to which power could be consumed. The limitation on consumed power and its adverse effect on spectral efficiency was mitigated using a Semi-Markov decision-making process along with the deactivation algorithm [11]. The spectral efficiency was improved by 38.5%, and the energy efficiency was improved by 19.2%. The use of the proposed sleep-mode algorithm showed an improvement in throughput by 34% compared to the non-sleep mode variant. The study, however, considered only the OFDMA-based HCN. A particle swarm optimization algorithm was used to find a tradeoff between SE and EE in a simulated eco-friendly cellular network [5]. The experiment focused on 5G base stations that could be turned on/off at various levels of instantaneous traffic load conditions. The investigation yielded an energy saving of up to 3.53 kW per day at a data rate of 22.4 Gbps. The data rate achieved was 80.64 Mbps, with full coverage of the entire network. The area spectral efficiency was investigated from a base station's perspective to emulate a practical multi-user scenario in a heterogeneous cellular network [12].

Results have consistently shown that the spectral efficiency of HCNs improves with any increase in the density of small base stations within the macro area. Still, this improvement comes at the expense of increased energy consumption or deteriorating energy efficiency. In a related study, the area spectral efficiency and energy efficiency were jointly optimized using the firefly algorithm in a two-tier heterogeneous cellular network to derive the optimal system parameters for any weight of area spectral efficiency and energy efficiency [13]. The study showed that increasing the number of users in the network made the optimization problem more challenging to solve, indicating the need for more physical resource blocks to meet the increased demand for spectral resources.

The existing research has shown a tradeoff between SE and EE in HCNs that can be optimized. Still, to the best of the authors' knowledge, the current literature does not provide any numerical analysis of the relationship between the SBS density and SBS transmit power with the energy-spectral-efficiency (ESE) of a sleep-mode activated HCN at various traffic levels. This research study seeks to answer the question of the

numerical implication of optimizing the ESE of a sleep-mode enabled HCN on the density and transmit power of randomly deployed SBSs at various network traffic levels.

### 3 Methodology

#### 3.1 The Heterogeneous Cellular Network Model

It is assumed that the base stations and user equipment in the heterogeneous cellular network are OFDMA enabled. All HCN BSs at all tiers work in the open-access mode. There is a perfect channel estimate for all transmitters within the HCN. The macro base stations are distributed using the Poisson point process (PPP). The macro base station is independently distributed with density  $d_N$ . The macrocell has a radius  $R_N$ . All users can connect to the macro base station (MBS) anywhere within the macrocell. The distance between the UE and the MBS is  $r_N$ . The probability density function (PDF) of the UEs within the macro cell becomes:

$$Z_M(r_N) = 2\pi d_N r_N exp(-d_N \pi r_N^2), r_N \epsilon(0, R_N)$$
(1)

The small base stations are distributed using the Poisson point process (PPP). The small base stations are independently distributed within the macrocell with density  $d_j$ . The small cell base stations improve the coverage probability of the macrocell. The small cell has a radius  $R_j$ . The small cell improves the network's throughput, especially when mobile traffic is high. Each small cell user can connect to the nearest SBS when it is within the proximity of an active SBS. The distance between the UE and an active SBS is  $r_j$ . The probability density function (PDF) of the UEs within the active small cell becomes:

$$Z_{\mathcal{S}}(r_j) = 2\pi d_j r_j \exp\left(-d_j \pi r_j^2\right), r_j \in \left(0, R_j\right)$$
(2)

The PDF of any UE's distance from the BSs of all tiers within the HCN becomes:

$$Z_i(r) = 2\pi d_i r_i \exp\left(-\pi d_i r_i^2\right), r \in (0, R_i)$$
(3)

#### 3.2 Coverage Probability of the Two-Tier Heterogeneous Cellular Network

The user may connect to the MBS of the first tier or the SBSs of the second tier. The UEs are assumed to know the distance of all BSs from all tiers within its proximity. The UEs use the minimum distance  $(\min\{a_ir_i\})$  to select a BS for connection.  $r_i$  represents the relative distance between UE and all BSs within its proximity.  $a_i$  represents the bias.

The probability of the UE connecting to any BS of tier *i* becomes:

$$P_c = P(a_i r_i < a_l r_l \forall l \neq i) = \int_{r=0}^{\infty} Z_i(r) (P(a_i r_i < a_l r_l \forall l \neq i)) dr$$

$$\tag{4}$$

 $a_l r_l$  are the relative distances of other BSs in the HCN to the UE.

#### 3.3 The Mobile Traffic Profile

The real-world traffic profile shows more traffic during the day (10:00–23:00 h) and less traffic at night (00:00–09:00 h). It is assumed that the actual values of traffic are continuously monitored and used to update the normalization scale to reflect its real normalized value [5]. SBSs are expected to be turned off during low traffic periods while the MBS remains active. The normalized range of values for high traffic is  $0.71 \le u \le 1$ . The normalized range of values for high traffic is  $0.5 \le u \le 0.7$ . The normalized range of values for high traffic is 0.49.

#### 3.4 The Small Base Station Sleeping Strategy

The small base stations in the HCN can be put to sleep based on mobile traffic demands and mobile user activity. The two modes of putting SBS to sleep considered in this study are random sleep mode and strategic sleep mode.

#### 3.5 Random Sleep Mode

In this mode, the SBSs in the HCN is put to sleep randomly. The power consumed by the BS in sleep mode is  $P_{sleep}$ . The MBS and selected SBSs are kept awake with a transmission power that compensates for the sleeping activity within the HCN. Bernoulli trial was used to model sleeping in the random sleep mode. The probability that a base station is independently operating, active, or awake is given as u. Thus the likelihood that an SBS in the HCN is asleep is 1 - u, independently. In random sleep mode, the average total power consumption in the HCN is expressed as:

$$C_R = d_j u \left( P_{r,j} + \Delta_j \beta P_j \right) + d_j (1 - u) P_{sleep}$$
<sup>(5)</sup>

 $P_{sleep} < P_{r,j}$  and  $C_R$  is the average power consumption for a random sleep mode enabled HCN.  $P_{r,j}$  is the static power of the SBS.  $\beta P_j$  is the power of radio-frequency output of the SBS.  $\Delta_j$  represents the slope of the load-dependent power consumption for the SBS.  $d_j$  is the stochastic density of the SBS.

#### 3.6 Strategic Sleep Mode

It is dynamic and considers the activity of mobile equipment users within the HCN. When the level of activity in the HCN is low or high, the SBSs are put to sleep according to the function, I : [0, 1] Which represents the activity level of the coverage area of the HCN. The activity level (*x*) determines the level of operation of the SBSs. The SBSs are kept awake with probability I(x) and put to sleep with probability

1 - I(x), independently. The strategic sleep mode is load-aware and location-aware. It can model the traffic profile and user location-based activity into the HCN's energy optimization process. The average power consumption using strategic sleep mode becomes:

$$C_S = d_j E\{I\} \left( P_{s,j} + \Delta_j \beta P_j \right) + d_j (1 - E\{I\}) P_{sleep}$$
(6)

 $C_S$  is the average power consumed by the SBSs of the HCN in strategic sleep mode.  $E\{I\}$  is the statistical expectation that an SBS is awake.  $P_{s,j}$  is the static power of the SBS.

#### 3.7 The SINR Model

The UE is assigned orthogonal carriers. The total bandwidth and power are shared among the UE in the network. Therefore, the general equation for the *SINR* of any UE in the HCN network is given by:

$$SINR_i = \frac{P_i G_i^2}{N_o W} \tag{7}$$

#### 3.8 The SINR for Small Cell Users

Every subchannel  $b_j$  in the small cell is occupied by only one user. Therefore the *SINR* of each user within the coverage of the SBS *j* becomes:

$$SINR_{i,j}^{OF,b_j} = \frac{\lambda_j^{b_j} P_j^{b_j} g_{1,j}^{b_j}}{N_a b_i}$$

$$\tag{8}$$

 $SINR_{i,j}^{OF,b_j}$  is the signal-plus-interference-to-noise ratio of any user assigned an orthogonal carrier  $b_j \in W_J$  in small cell *j*.

#### 3.9 The SINR for Macro Cell Users

Every subchannel  $b_N$  in the macrocell is occupied by only one user. Therefore the *SINR* of each user within the coverage of then MBS *N* becomes:

$$SINR_{i.N}^{OF,b_n} = \frac{\lambda_N^{b_n} P_N^{b_n} g_{1,N}^{b_n}}{N_o b_N}$$

$$\tag{9}$$

 $SINR_{i,N}^{OF,b_n}$  is the signal-plus-interference-to-noise ratio of any user assigned an orthogonal carrier  $b_N \in W_N$  in macrocell N.

#### 3.10 Sum Rate for Small Cell and Macro Cell Users

The sum rate is expressed mathematically as:

$$R_{b_n} = P_c Log(1+\rho) \tag{10}$$

 $R_{b_n}$  is the throughput on channel *n*.  $P_c$  is the coverage probability and  $\rho$  is the signal-plus-interference-to-noise-ratio.

The total throughput  $(R_T)$  of the HCN network model becomes:

$$R_T = R_N + R_J \tag{11}$$

 $R_N$  and  $R_J$  represent the sum rate of the macrocell and small cells, respectively.

#### 3.11 The Energy-Spectral-Efficiency (ESE) the HCN

The spectral efficiency is given as:

$$SE_{OF} = \frac{R_T^{OF}}{W} \tag{12}$$

Where  $R_T^{OF}$  is the throughput of the two-tier HCN.

The energy efficiency of the HCN for random sleep mode is given as:

$$EE_{ran}^{OF} = \frac{R_T^{OF}}{\left[d_j u \left(P_{r,j} + \Delta_j \beta P_j\right) + d_j (1-u) P_{sleep}\right] + \left(P_{s,N} + \beta \Delta_N P_N\right)}$$
(13)

The energy efficiency of the HCN for strategic sleep mode is given as:

$$EE_{stra}^{OF} = \frac{R_T^{OF}}{\left[d_j E\{I\} \left(P_{s,j} + \Delta_j \beta P_j\right) + d_j (1 - E\{I\}) P_{sleep}\right] + \left(P_{s,N} + \beta \Delta_N P_N\right)}$$
(14)

Therefore, the ESE for the HCN in random sleep mode becomes:

$$ESE_{ran}^{OF} = SE_{OF} \frac{W}{\left[d_{j}u\left(P_{r,j} + \Delta_{j}\beta P_{j}\right) + d_{j}(1-u)P_{sleep}\right] + \left(P_{s,N} + \beta\Delta_{N}P_{N}\right)}$$
(15)

The ESE for the HCN in strategic sleep mode becomes:

$$ESE_{stra}^{OF} = SE_{OF} \frac{W}{\left[d_j E\{I\} \left(P_{s,j} + \Delta_j \beta P_j\right) + d_j (1 - E\{I\}) P_{sleep}\right] + \left(P_{s,N} + \beta \Delta_N P_N\right)}$$
(16)

#### 3.12 The ESE Optimization Problem

Maximize

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$$EE = \zeta_{EE} \tag{17}$$

Maximize

$$SE = \zeta_{SE} \tag{18}$$

Subject to:

$$C1: \rho_{i,j} \ge \rho_{required}$$

$$C2: \rho_{i,n} \ge \rho_{required}$$

$$C3: \sum_{j=1}^{J} \sum_{i=1}^{I} \beta P_{i,j} \le \sum_{j=i}^{J} P_{max}^{J}$$

$$C4: d_{j,min} \le d_j \le d_{j,max}$$

 $P_{max}^{J}$  - The maximum transmit power of the SBS.

 $d_i$  - Density of SBS.

EE, SE - Energy efficiency and spectral efficiency, respectively.

 $\rho_{required}$  - The SINR threshold for SBS UE and MBS UE.

C1, C2 - Ensures the data rates of all UE do not fall below the pre-set threshold.

C3 - Ensures power allocated do not exceed the maximum for all SBSs combined.

C4 - Ensures that the allowable density of SBS is not exceeded.

 $\zeta_{EE}$  – The HCN energy efficiency using a selected multiple access technique.

 $\zeta_{SE}$  – The HCN spectral efficiency using a selected multiple access technique.

An algorithm (Algorithm 1) that simultaneously maximizes the SE and EE of the two-tier HCN was developed and tested using MATLAB2018b. The algorithm optimizes the SE and EE of a two-tier heterogeneous cellular network subject to the variables the network operator wishes to control. The developed algorithm allows the network operator to tune the network's parameters to attain the simultaneous levels of EE and SE needed from the HCN. The algorithm was based on a modified nature-inspired particle swarm optimization technique that simultaneously considers several optimization possibilities until a Pareto-optimal front is achieved. The Pareto-optimal front contains the possible solutions to the multiobjective optimization problem in Eqs. 17 and 18. The Pareto-optimal front provides points not dominated by other points outside the front.

Algorithm 1: Sleep Mode Algorithm
<b>Input:</b> Normalize traffic, time(hourly), SBS density( $d_i$ ), MBS density ( $d_N$ ),
Network simulation parameters.
<b>Output:</b> Average power consumption ( <i>C</i> ), coverage probability ( $P_c$ ), ESE
Pareto-optimal front for energy and spectral efficiency maximization
for hourly values of normalized traffic, do
Calculate SBS operating probability:
for random sleep mode, do
Compute the average power consumption, $C_R$
Determine the random sleep mode coverage probability, $P_{c,ran}$
Optimize ESE using particle swarm technique
for strategic sleep mode, do
Compute the average power consumption, $C_S$
Determine the strategic sleep mode coverage probability, $P_{c,stra}$
Optimize ESE using particle swarm technique
end for
end for
Display average power consumption, coverage probability, and ESE Pareto-optimal
front for random and strategic sleep modes
end for

### 4 Results and Discussion

The two-tier HCN is evaluated through numerical simulations in MATLAB2018b. The obtained results are thoroughly discussed. The simulation parameters are obtained from [6] and [7] and are presented in Table 1.

Parameter	Value
MBS transmit power $(\beta P_N)$	31 W
SBS transmit power $(\beta P_j)$	Variable
MBS fixed power consumption	130 W
SBS fixed power consumption	4.8 W
Traffic distribution	Normalized
Total number of channels	10
The bandwidth of each sub-channel (b)	30 kHz
Path loss exponent $(\alpha)$	4
SBS sleep mode power consumption $(P_{sleep})$	2.9 W
Number of channels allocated to MBS	6
Number of channels allocated to SBS	4
SBS density $(d_j)$	Variable
MBS density $(d_N)$	$10^{-1} \text{ m}^{-2}$
SINR threshold of small cell $(\rho_j)$	Variable
The slope of load-dependent power consumption of SBS ( $\Delta_j$ )	4.7
The slope of load-dependent power consumption of MBS $(\Delta_N)$	8.0

Table 1. Simulation parameters

# 4.1 Energy Spectral Efficiency (ESE) of OFDMA Based HCN with Varying MBS Power

The plot in Fig. 1 gives a glimpse into the tradeoff between energy efficiency and spectral efficiency for OFDMA based HCN in no-sleep mode. When the transmit power of the MBS is varied, the full range of values for the tradeoff between energy efficiency and spectral efficiency can be seen from the point where all base stations, including the MBS, are shut off, at the origin (the point where SE and EE are zero). The energy efficiency rises almost linearly with the spectral efficiency until the energy efficiency reaches its maximum value at  $3.3 \times 10^{10}$  bits/s/m<sup>2</sup>/W. Beyond the maximum value for energy efficiency, the tradeoff between EE and SE becomes noticeable. The spectral efficiency continues to increase till it reaches its maximum value at  $2.52 \times 10^5$  bps/Hz, but at the cost of a 22% drop in energy efficiency. After the maximum EE is achieved, the tradeoff shows that the addition of SBSs to the network needs to be optimized to ensure that the overall energy and spectral efficiency outlook maintains the profile that the network provider can support.

Figure 2 shows the net energy and spectral efficiency tradeoff in the HCN when the power of the SBS is varied while the power of the MBS is kept constant. The values of SE and EE in Fig. 2 are unoptimized, and a clear tradeoff exists between the EE and SE of the HCN. The peak EE attained by all three sleep modes is about  $2.7 \times 100^1$  bits/s/m<sup>2</sup>/W. The HCN achieves the highest EE in strategic sleep mode, while the highest SE is achieved in no-sleep mode. The improvement in EE in strategic or random sleep modes is because some base stations are put to sleep according to the level of traffic in the HCN. In sleep mode, interferences are minimized, and the HCN can achieve a satisfactory level of network throughput. All deployed SBSs are kept awake in no-sleep mode regardless of the network's traffic level. Thus, the amount of information sent per watt of energy consumed is reduced due to increased network interference. In no-sleep mode, the network compensates for increased interference by allowing all SBSs to transmit at a higher power level leading to a poor tradeoff between energy and spectral efficiency.

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Fig. 1. ESE of OFDMA based HCN with Macro Base Station (MBS) power varied.



Fig. 2. ESE of OFDMA based HCN with SBS power varied.

# 4.2 Random Sleep-Mode ESE Optimization of OFDMA-Based HCN Using Proposed Optimization Algorithm at High Traffic Levels

The result of the simulation of random sleep-mode energy and spectral efficiency optimization for OFDMA-based HCN at high traffic levels is shown in Fig. 3. The Pareto-optimal front is scanty, probably because some base stations are put to sleep in random sleep mode. Another reason for the sparse plot may be the orthogonal nature of sharing spectrum using OFDMA, where only one user is assigned a subchannel at a time. The Pareto-optimal front was got by setting the traffic to a high level, varying the SBS density  $d_j$  and varying the transmit power of the SBS,  $\beta P_j$ . The other parameters such as MBS transmit power,  $\beta P_N$  and the SINR threshold,  $\rho$  were fixed. From Table 2, the optimum SE and EE attained by the OFDMA-based HCN was 2.1392 × 10<sup>6</sup> bps/Hz and 1.7135 × 10<sup>11</sup> bits/s/m<sup>2</sup>/W respectively.

The corresponding optimal SBS density and SBS transmit power that achieves the maximum SE and EE for random sleep-mode OFDMA-based HCN at high traffic levels were  $0.0890 \,\mathrm{m}^{-2}$  and  $0.9923 \,\mathrm{W}$ . The result obtained in random sleep mode at high traffic levels is the solution to the maximization problem of Eq. 17 and Eq. 18. It reveals the density of SBS and the power at which the SBS should transmit to achieve the optimum levels of SE and EE in the HCN. The unoptimized result for ESE optimization in random sleep mode in Fig. 2 shows a much lower level of SE and EE.



Fig. 3. Random sleep mode ESE optimization of OFDMA-Based HCN using proposed PSO optimization algorithm at high traffic levels.

### 4.3 Random Sleep-Mode ESE Optimization of OFDMA-Based HCN using Proposed Optimization Algorithm at Low Traffic Levels

The result of the random sleep-mode energy simulation and spectral efficiency optimization for OFDMA-based HCN is shown in Fig. 4. The Pareto-optimal front is convex and shows a high degree of freedom in the selection of SBS density,  $d_i$  and SBS transmit power,  $\beta P_i$  to achieve the desired energy and spectral efficiency within the HCN. At low traffic periods and in random sleep mode, most SBSs are put to sleep randomly. The remaining SBSs available for offloading of traffic are few and scattered. UEs tend to connect to SBSs at low traffic levels only when the SBS is very close. The network operator tries to encourage connections to SBSs at low traffic levels through an increment in the transmission power of the remaining SBSs, but most UEs would still connect instead to the MBS. The preference for connection to the MBS instead of SBS at low traffic periods is the reason for the convex Pareto-optimal front in Fig. 4. There is the liberty to save as much energy as desired by lowering the SBS transmission power or encouraging more UEs to connect to nearby SBSs by increasing the transmit power of the remaining SBSs. The increase of SBSs transmit power causes a reduction in the energy efficiency and an increase in the spectral efficiency. A drop in the transmit power of the remaining SBSs would increase the energy efficiency at the expense of reduced spectral efficiency. From Table 2, the solution of the optimization problem for random-mode OFDMA -based HCN was an SBS transmit power of 0.0462 W and an SBS density of 0.6871  $m^{-2}$  which corresponds approximately to a SE and EE of  $2.5933 \times 10^5$  bps/Hz and  $2.6332 \times 10^{10}$  bits/s/m<sup>2</sup>/W. The Pareto optimal front in Fig. 5 was obtained for comparison using the ParetoSearch algorithm in MATLAB 2018b. The negative values on the plot axes show that the objective function SE and EE functions are maximized. The Pareto optimal front obtained was also non-convex. In comparison with the proposed PSO algorithm, the ParetoSearch did not provide the exact location of the optimal values of SBS density and SBS transmit power that gives the optimum values of SE and EE. Thus, the location of the solution to the optimization problem for the ParetoSearch algorithm was chosen at random and was found to be a little lower than the solution obtained using the proposed PSO algorithm, as seen in Table 2. The ParetoSearch algorithm generated the Pareto optimal front for the HCN only at low traffic levels. The ParetoSearch algorithm could not create the set of nondominated points at high traffic levels.



**Fig. 4.** Random sleep mode ESE optimization of OFDMA-based HCN using proposed PSO optimization algorithm at low traffic levels.



Fig. 5. Random sleep mode ESE optimization of OFDMA-based HCN using ParetoSearch algorithm at low traffic levels.

Parameters				
MBS Transmit Power ( $\beta P$	N) = 31 Watts			
SBS Transmit Power $(\beta P)$	= 0 - 1 Watts			
Traffic Level = Low: 0.1 - 0	0.15; High: 0.8 – 0.8	85; Moderate: 0.4	4 - 0.5	
<b>SBS Density</b> $(d_j) = 0.01$	$-0.09 \ (m^{-2})$			
MBS Density $(d_N)$	$= 10^{-2} (m^{-2})$			
SINR Threshold ( $ ho$ )	$= 10^{-5}$			
	Optimum Paran	neters		
Algorithm, Traffic Levels and Sleep Mode	SBS Density $(m^{-2})$	SBS Transmit Power (W)	Spectral efficiency ( <i>bps/Hz</i> )	Energy Efficiency bits/s/m <sup>2</sup> /W
Proposed PSO at Low Traffic Levels and in Random Sleep-Mode	0.0462	0.6871	$2.5933 \times 10^5$	$2.6332 \times 10^{10}$
ParetoSearch algorithm at Low Traffic Levels and in Random Sleep-Mode	0.0606	0.7063	$2.5578 \times 10^5$	$2.5763 \times 10^{10}$
Proposed PSO at Low Traffic Levels and in Strategic Sleep-Mode	0.0456	0.4453	$2.5752 \times 10^5$	$2.6248 \times 10^{10}$
Proposed PSO at High Traffic Levels and in Random Sleep-Mode	0.0890	0.9923	$2.1392 \times 10^{6}$	$1.7135 \times 10^{11}$
Proposed PSO at High Traffic Levels and in Strategic Sleep-Mode	0.0899	0.9965	$2.187 \times 10^{6}$	$1.7428 \\  imes 10^{11}$

#### 4.4 Strategic Sleep-Mode ESE Optimization of OFDMA-Based HCN with Varying SBS Density and SBS Transmit Power at High Traffic Levels

The result of the simulation of the strategic sleep-mode ESE optimization of the OFDMA-based HCN is shown in Fig. 6. The Pareto-optimal front was got by fixing the SINR threshold and varying SBS density and SBS transmit power. The Pareto-optimal front is non-convex and shows a simultaneous maximization of the SE and EE. The Pareto-optimal front for strategic sleep-mode at high traffic levels is nearly linear, although there are still gaps in the front. In strategic sleep mode, the SBSs are either awake or put to sleep by considering the temporal and spatial variation in user-generated traffic. Thus, the optimization problem for the strategic sleep mode is different from what is obtained using random sleep mode. From Fig. 6, the optimum values of SE and EE are  $2.187 \times 10^6$  bps/hz and  $1.7428 \times 10^{11}$  bits/s/m<sup>2</sup>/W respectively, for the strategic sleep mode at high traffic levels.

The strategic sleep mode's optimum SE and EE achieved at high traffic levels are 2% higher than the optimum value for SE and EE in OFDMA-based HCN using random sleep-mode. The reason for the disparity in SE and EE between the strategic sleep mode and random sleep mode is the responsiveness of the strategic sleep mode to spatial variations in traffic. The responsiveness of the strategic sleep mode to both temporal and spatial variations in traffic is seen in the solution to the optimization problem for the required SBS density (0.0899 m<sup>-2</sup>) and transmit power (0.9965 W) that maximizes the EE and SE of the OFDMA-based HCN, as shown in Table 2. The SBS density and SBS transmit power values for the strategic sleep mode is 1% higher for the SBS density and almost 0.4% higher for the SBS transmit power. This result indicates that network operators should consider using strategic sleep-mode for HCNs if the quality of service of all users in the network does not fall below a given threshold and thus, save energy and improve the throughput of the network where it is needed.



Fig. 6. Strategic sleep mode ESE optimization of OFDMA-based HCN using proposed optimization algorithm at high traffic levels.

#### 4.5 Strategic Sleep-Mode ESE Optimization of OFDMA-Based HCN with Varying SBS Density and SBS Transmit Power at Low Traffic Levels

The result of optimizing the strategic sleep-mode energy and spectral efficiency of OFDMA-based HCN at low traffic levels with varying SBS density and SBS transmit power is shown in Fig. 7. The Pareto-optimal front was obtained by fixing the SINR

threshold values of the MBS and SBS and varying the SBS density, and SBS transmit power. The Pareto-optimal front was convex, showing a tradeoff between SE and EE. The tradeoff was caused by UEs connecting to the MBS instead of nearby SBSs due to the higher received signal strength of the MBS at low traffic levels. In strategic sleep mode and at low traffic levels, the network operator can conserve more energy or increase the network's throughput. From Table 2, the value of the SBS density and SBS transmit power that optimizes the SE ( $2.5752 \times 10^5$  bps/Hz) and EE ( $2.6248 \times 10^{10}$  bits/s/m<sup>2</sup>/W) of the OFDMA-based HCN is given as 0.0456 m<sup>-2</sup> and 0.4453 W respectively.

In strategic sleep mode and at low traffic levels, the OFDMA-based HCN achieves a slightly lower optimal SE and EE than the random sleep mode at low traffic levels. The lower SE and EE in the OFDMA-based HCN result from the orthogonal nature of resource allocation and the adaptability of the strategic sleep mode to spatial variations in traffic. The optimum SE and EE for strategic sleep-mode in the OFDMA-based HCN were achieved at an SBS transmit power and SBS density of 54% and 1% lower than that of the random sleep-mode technique at low traffic levels.



Fig. 7. Strategic sleep mode ESE optimization of OFDMA-based HCN using proposed optimization algorithm at low traffic levels.

#### 5 Conclusion

This research study has shown that stochastic deployment of SBSs leads to SE and EE inefficiencies if it is not well managed. The study considered two sleep modes (random and strategic) to enable the conservation of energy and the preservation of the required QoS of the network at all traffic levels. The strategic sleep mode achieves the better optimum values of SE and EE at high and low traffic levels in OFDMA-based HCNs. A weighted-sum modified PSO algorithm was proposed to simultaneously maximize the EE and SE. The unoptimized values of the SE and EE of the OFDMA-based HCN were lower than the optimized values. The proposed optimization algorithm was compared with the ParetoSearch algorithm. The proposed PSO algorithm found the Pareto optimal front for all traffic levels, but the ParetoSearch could only get the Pareto optimal front at low traffic levels. The result of the study additionally showed that it is inefficient to deploy small base stations without some form of sleeping techniques that put underutilized small base stations to sleep at low traffic levels. The improvement in the throughput and the amount of energy saved were considered in random and strategic sleep modes. The proposed PSO algorithm provided the values of the SBS density and SBS transmit power that optimized the SE and EE of the OFDMA-based HCN. Regardless of the density of small base stations deployed, the strategic sleep mode provided the best energy savings due to its temporal and spatial adaptability to network traffic levels.

#### 6 Future Work

The optimization technique explained in the paper would be extended to cloud radio access networks (C-RANs) and non-orthogonal multiple access techniques.

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