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RESEARCH ARTICLE

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Particle swarm optimization of the spectral and energy efficiency of an SCMA-based heterogeneous cellular network

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Abstract

Background: The effect of stochastic small base station (SBS) deployment on the energy efficiency (EE) and spectral efficiency (SE) of sparse code multiple access (SCMA)-based heterogeneous cellular networks (HCNs) is still mostly unknown.

Aim: This research study seeks to provide insight into the interaction between SE and EE in SBS sleep-mode enabled SCMA-based HCNs.

Methodology: A model that characterizes the energy-spectral-efficiency (ESE) of a two-tier SBS sleep-mode enabled SCMA-based HCN was derived. A multiobjective optimization problem was formulated to maximize the SE and EE of the SCMA-based HCN simultaneously. The multiobjective optimization problem was solved using a proposed weighted sum modified particle swarm optimization algorithm (PSO). A comparison was made between the performance of the proposed weighted sum modified PSO algorithm and the genetic algorithm (GA) and the case where the SCMA-based HCN is unoptimized.

Results: The Pareto-optimal front generated showed a simultaneous maximization of the SE and EE of the SCMA-based HCN at high traffic levels and a convex front that allows network operators to select the SE-EE tradeoff at low traffic levels flexibly. The proposed PSO algorithm offers a higher SBS density, and a higher SBS transmit power at high traffic levels than at low traffic levels. The unoptimized SCMA-based HCN achieves an 80% lower SE and a 51% lower EE than the proposed PSO optimized SCMA-based HCN. The optimum SE and EE achieved by the SCMA-based HCN using the proposed PSO algorithm or the GA are comparable, but the proposed PSO uses a 51.85% lower SBS density and a 35.96% lower SBS transmit power to achieve the optimal SE and EE at moderate traffic levels.

Conclusion: In sleep-mode enabled SCMA-based HCNs, network engineers have to decide the balance of SBS density and SBS transmit power that helps achieve the desired SE and EE.

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1 INTRODUCTION

The overwhelming demand for capacity and bandwidth led to the deployment of small cells within legacy macrocells to increase network throughput and compensate for network coverage holes. Network demands for video streaming, cloud services, social media, machine-type connections, and virtual reality caused the recent spike in data traffic. The network traffic is dependent on the number of connected devices and the type of service demanded by the users.[1] The mammoth increase in the number of mobile devices purchased worldwide and the continued roll-out of data-intensive services also caused massive demand for network bandwidth. Heterogeneous cellular networks (HCNs) proffers a means to help meet the ever-increasing demand for more network capacity.[2]

HCNs provide a feasible means of increasing network throughput.[3] Energy consumption increases with the random deployment of small base stations (SBSs), and cellular network operating burden in terms of energy costs grows. The throughput gains are also limited by the efficiency of access to the limited spectrum and the resources available for capital expenses on heterogeneous network technologies.[4] These limitations of HCNs highlight the need to explore other multiple access techniques to improve spectral efficiency (SE) and help network operators to manage the tradeoff between energy efficiency (EE) and SE in HCNs.[5]

The algorithms used to solve energy and SE problems are usually complex and computationally time-consuming. Time-consuming solutions are less favored than more straightforward and lower computation-time alternatives. Algorithms for EE in HCN are sometimes formulated to provide an optimal solution with some form of independence at all base stations (BSs), including any coordinating BS. Such answers are usually distributive and help provide a way to allocate power within an HCN to minimize interference. Power consumption is minimized in HCNs using distributive power allocation algorithms that search for the optimal operating condition that maximizes EE. There have been significant performance gains from developing distributive HCN power allocation algorithms.[6] Researchers used a soft frequency reuse scheme to optimize SE in a HCN in Reference 7. The EE of soft frequency reuse-based HCN was maximized using a global EE index. The resulting non-concave EE maximization problem was solved using successive approximation, Lagrange dual multipliers, Karush-Kuhn-Tucker conditions, and a fractional program. The investigation resulted in a global EE optimization algorithm for searching the optimum EE point for HCNs. The researchers proposed a mathematical framework for analyzing the SE and EE in a HCN in Reference 8. The exact EE and SE expressions were derived using a moment generating function. The result showed how SE and EE could be improved using regulated power scheduling for all network users.

Despite the tremendous work that has gone into improving the spectral and energy efficiency (SE-EE) tradeoff performance of HCNs, the existing literature does not have very much to reveal about the SE-EE performance of sparse code multiple access (SCMA) based HCNs. The SCMA, being a code-domain multiple access technique, has its unique effect on the SE-EE tradeoff in HCNs. To the best of the authors' knowledge, a detailed analysis of the impact of SBS sleep-mode on the SE-EE characteristic of an SCMA-based HCN has not been studied. The existing literature provides too little information about the SBS density and SBS transmit power level at various network traffic levels that achieve the optimum energy-spectral-efficiency (ESE). Algorithms to optimize the simultaneous maximization of the EE and SE of SCMA-based HCNs are also missing in the existing literature. This research study looks closely at the SE-EE dynamics in an SCMA-based HCN incorporating an SBS sleeping technique. This research study also proposes a means of optimizing the SE-EE tradeoff in an SCMA-based HCN using the weighted sum modified particle swarm optimization (PSO) technique. The research questions that were asked to accomplish the goals of this research study include:

1. How may the uncoordinated deployment of SBSs in an SCMA-based HCN be modeled?
2. What are the leading network parameters that affect the SE-EE tradeoff in an SCMA-based HCN with stochastic SBS deployment?
3. In what ways does the SE-EE tradeoff of an SCMA-based HCN behave in SBS sleep mode?
4. What are the numerical values of SBS density and SBS transmit power at various network traffic levels needed to achieve optimum ESE in a sleep-mode activated SCMA-based HCN?

The following are the contributions this research study has made to the existing body of knowledge:

1. A model for characterizing the SE-EE tradeoff in an SCMA-based HCN.
2. An algorithm that can maximize the SE and EE of an SBS sleep-mode enabled SCMA-based HCN simultaneously.
3. An insight into the SE-EE tradeoff behavior of an SCMA-based HCN under strategic SBS sleep-mode conditions.

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The remaining part of the article is organized in this format. Section 2 reviews related works. Section 3 discusses the collective energy and SE outlook in SCMA-based HCNs, and the proposed algorithm used to solve the energy spectral efficiency (ESE) tradeoff in SCMA-based HCNs. The simulation results are discussed in Section 4. The article is then concluded, and references are provided.

2 | RELATED WORKS

Downlink Joint user association and power allocation for an SCMA-based cloud radio access network (C-RAN) were investigated by Farhadi Zavleh and Bakhshi.[9] The user association and power allocation problems were solved using an iterative algorithm. This research study did not consider the simultaneous maximization of the SE and EE. It also did not investigate the effect of sleeping techniques on the network. The C-RAN system model[7] did not explicitly use the architecture to solve the user association and power allocation problem but focused on the SCMA technique.

The need for improving SE through nonorthogonal multiple access (NOMA) techniques was addressed by Ding et al,[1] and emphasis was placed on the application of NOMA in current long term evolution (LTE) advanced and fifth-generation (5G) networks. The lower bound on the maximum number of users that can utilize a single radio resource in the uplink of an SCMA-based network was derived by Gamal et al[10] and solved using the difference of convex functions and swap matching.

The range of applications for NOMA techniques has been extended to cognitive radio networks, and the SCMA has found use in the joint optimization of several cognitive radio network parameters. The peculiar advantage of the SCMA technique has been highlighted to include multi-dimensional sparsity and more diversity.[11] In multiple-input-multiple-output (MIMO) systems, the SCMA provided significant performance gains over orthogonal frequency division multiple access (OFDMA) based MIMO systems.[12] Thus, SCMA has shown promise as a multiple access technique in future networks.

The SCMA technique has seen further improvement through the use of deep learning. In research conducted by Lin et al,[13] deep learning was used to improve the accuracy of codebooks and reduce the complexity of decoding at the receiver. The deep learning assisted SCMA system was found to outperform conventional SCMA systems significantly. Researchers in Reference 14 carried out a practical implementation of the transmission and reception process for SCMA-based networks. Field programmable gate array (FPGA) was used to design the physical system for transmitting and decoding an SCMA-based message. The result of the experiment showed that the design, based on FPGA, Quarlus II, and ModelSim platform were good enough to be used in practice.

Multiobjective optimization problems (MOP) are formulated to study the tradeoff between SE and EE in 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 a sample frequency division multiplexing (FDM) nonorthogonal multiple access (NOMA)-based HCNs research, a MOP was formulated to study the tradeoff between EE and SE in a HCN.[14] 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. The MOP solution showed a superior performance to the conventional orthogonal multiple access (OMA) scheme. However, the study did not consider power allocation optimization for user equipment (UE) exclusively connected to the macro base station. A single-objective optimization problem (SOP) called a mixed-integer non-convex program was developed in a related study for EE optimization in the uplink for power domain (PD)-NOMA HCNs.[15] The solution to the optimization problem led to the development of a power controlled system-wide utility maximization algorithm. Future cellular networks thrive on fine-tuned spectral and energy-efficient systems. An experiment to analyze the SE-EE tradeoff in a two-tier HCN was carried out using a shared spectrum scenario. The investigation showed that improvement in SE using overlaid SBSs (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 and EE tradeoff. The multiobjective optimization problem was solved to yield the Pareto optimal tradeoff point 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.[16] The impact of varying mobile traffic demands on the EE-SE tradeoff was quantified and used to balance EE and SE at varying load conditions.

The weighted logarithmic utilities were maximized using an offloading tool to achieve the desired tradeoff between SE and EE in HCNs. The weighted logarithmic utilities served to set the desired SE-EE tradeoff. The goal was to attain SE-EE fairness using SE and energy consumption tradeoffs.[17] The ϵ-constraint method was used to solve the multiobjective optimization problem that maximizes the EE and SE.[18] The result was a two-stage iterative algorithm that converges quickly to

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the Pareto-optimal solution. In yet another research, PD-NOMA was used to design a spectrally efficient two-tier HCN.[19] The SE and EE problem was formulated as a joint optimization problem that was solved using successive convex approximation. The non-convex EE-SE problem was converted into two solvable convex sub-problems that separated the resource allocation problem from the power allocation challenge. A clustering model was used to formulate the power minimization problem to achieve the optimal received signal strength threshold and the tradeoff between SE and EE.[20] The result of the experiment showed that HCNs could be an energy-saving model for future networks.

The limited radio spectrum is accessed in diverse ways. There has been an evolutionary trend to devise more efficient ways of allowing multiple users to access the limited spectrum. In recent times, researchers have explored the idea of nonorthogonal multiple access (NOMA). Several NOMA techniques have been developed in the existing literature.[21,22] The SCMA, for example, is a NOMA technique that can deliver an improved bit error rate (BER) and higher SE than orthogonal multiple access (OMA) techniques.[23] The SCMA can be enhanced using a message-passing algorithm (MPA). A software and hardware version of the SCMA was implemented to show that the multiple access technique can achieve an encoding throughput of 1 Gbps and a throughput of 3.5 and 8 Gbps for software and hardware implementations respectively.[24] An advantage of the SCMA is its better coverage due to its spreading gain. The disadvantage of the SCMA is its need for highly complex decoders to extract the receiver's information signal. In many SCMA receiver designs, a tradeoff is made between complexity and bit error rate (BER).

The existing literature is full of works revolving around NOMA-based HCNs, but the SE and EE tradeoff for SCMA-based HCNs remains a research gap. At its core, the RAN architecture consists of remote radio heads, fronthaul links, and baseband unit (BBU) pools. Our research focused on the stochastic deployment of more SBSs within the original macro-cell. We focus on the simultaneous maximization of SE and EE in a HCN. The HCN may be redesigned to follow the C-RAN blueprint but the underlying need for more radio heads within the original macro-cell is universal.

3 | METHODOLOGY

The research method is described in detail. The EE-SE optimization problem is formulated and solved using a weighted sum modified particle swarm optimization (PSO) algorithm. Table 1 enumerates the mathematical notations used in this article.

3.1 | The heterogeneous cellular network model

The proposed system model consists of a macro cell with its macro base station and several small cells, each with its SBS. The SBSs can be put to sleep. The macro base station does not go to sleep. The decision to put base stations to sleep is made using the network traffic data maintained at the macro base station. In sleep mode, hibernation signals are sent randomly from the macro base station to SBSs or on the cell-activity level. As shown in Figure 1, the network implements SCMA that enables two users to share the same code block simultaneously. The network implements SCMA, allowing two users to share the same code block simultaneously. The network bandwidth W is shared orthogonally between the macro cell (b_n) and the small cells $\left(b_j\right)$ to minimize inter-cell interference. Each user device in the network can decode the SCMA signals $y_{a_i}, y_{b_i}, \text{ and} y_{c_i}$, sent from the base station of small cell-A, small cell-B, and macro cell-C, respectively. The unique message signal for each user device in the network is derived after a connection is made to the nearest base station. The decoded signals for small cell-A $\left[a_{s_{1,j}}, \ldots\ a_{s_{n,j}}\right]$, small cell-B $\left[b_{s_{1,j}}, \ldots\ b_{s_{n,j}}\right]$. And the macro cell $\left[c_{s_{1,N}}, \ldots\ c_{s_{n,N}}\right]$ are got after taking care of all interferences in the network.

It is assumed that the base stations and UE in the HCN are NOMA 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. Small scale fading, path loss, and shadowing affect the received signals within the HCN. The small scale fading follows the Rayleigh distribution model, and the path loss is assumed to be constant throughout 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 UEs within the macro cell's probability density function (PDF) becomes as written in Equation (1).

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TABLE 1 List of mathematical notations

Mathematical notations	
u	**Probability SBS is awake**
d_N	MBS density
ρ	SINR threshold
b	Subchannel
d_j	SBS density
W	Bandwidth
P_c	Coverage probability
R	Throughput
P_{sleep}	Power consumed by BS when it is asleep
βP_N	Static power of MBS
βP_j	Static power of SBS
Δ_j	The slope of load dependent power consumption of SBS
Δ_N	The slope of load dependent power consumption of MBS
λ_N	Coefficient of power allocated to subchannel in macro cell
λ_j	Coefficient of power allocated to subchannel in small cell
g_N	Gain of channel users in macro cell
g_j	Gain of channel users in small cell
δ	Noise density
j	Number of layers assigned to a user in the SCMA code block
r	Coding rate
E	Mathematical statistical expectation
Y	Normalize traffic
C	Average power consumption
$I(x)$	Strategic SBS operating probability
$O_B(x)$	Probability distribution function of random small cell user activity
α	Path loss exponent
r	Cell radius

$$Z_M\left(r_N\right) = 2\pi d_N r_N \exp\left(-d_N \pi r_N^2\right), \quad r_N \epsilon \left(0, R_N\right) \tag{1}$$

The SBSs are distributed using the PPP. The SBSs 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 PDF of the UEs within the active small cell becomes as written in Equation (2).

$$Z_S\left(r_j\right) = 2\pi d_j r_j \exp\left(-d_j \pi r_j^2\right), r_j \epsilon \left(0, R_j\right). \tag{2}$$

The PDF of any UE's distance from the BSs of all tiers within the HCN becomes as written in Equation (3).

$$Z_i(r) = 2\pi d_i r_i \exp\left(-\pi d_i r_i^2\right), r \epsilon \left(0, R_i\right). \tag{3}$$

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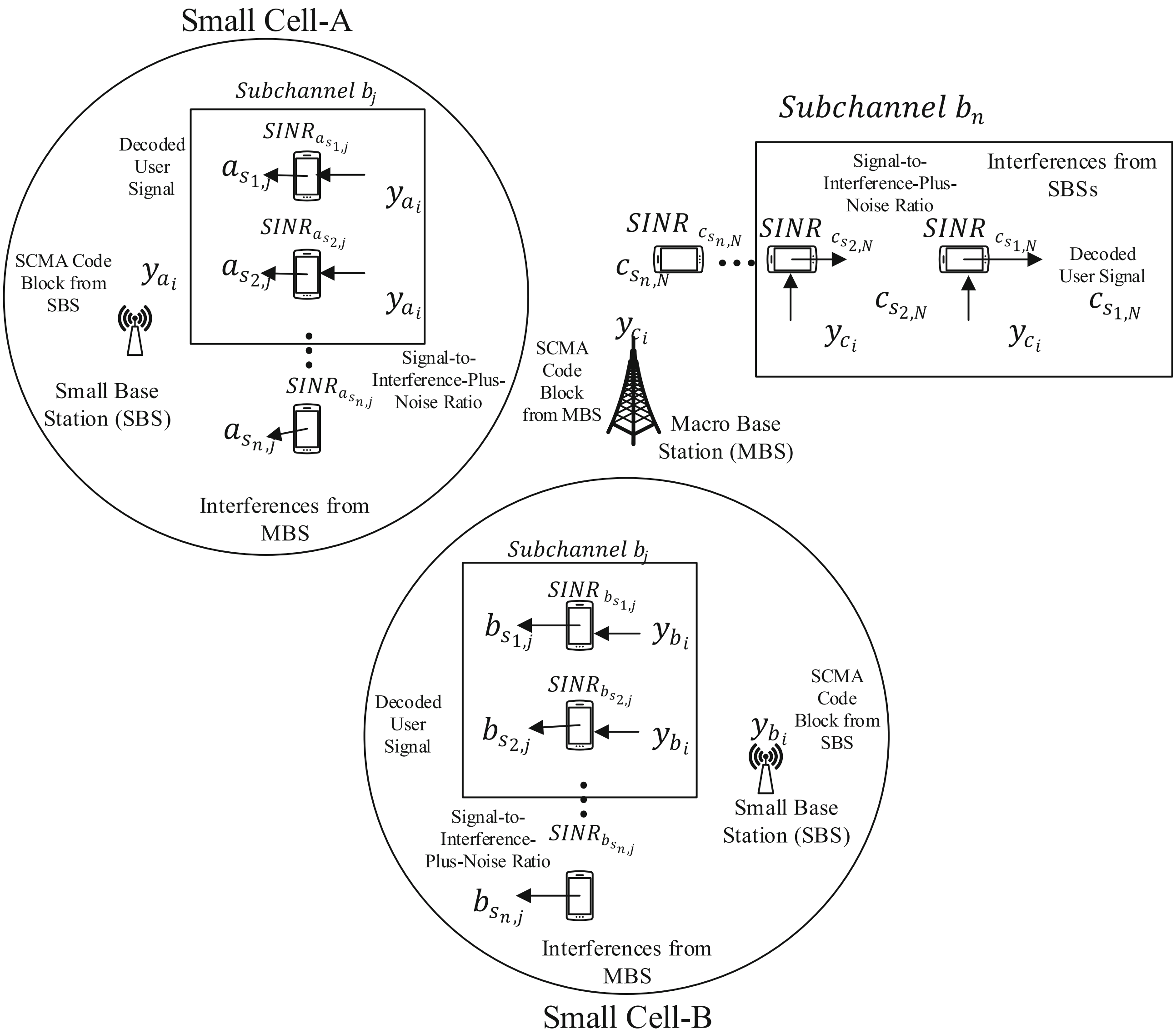

FIGURE 1 The heterogeneous cellular network model

Without loss of generality, the channel between the base stations and UEs are assumed to be Rayleigh fading channel. Therefore the signal received from the serving BS to the UE becomes a function of the multiple access technique employed. The signal power between the serving BS and UE is expressed in Equation (4).

$$\text{Signal Power} = hPr_i^{-\alpha}. \tag{4}$$

P is the transmit power of the serving BS, and h represents Rayleigh channel gain. The distance between the BS and the UE is r_i and α is the path loss exponent. The signal-to-interference-plus-noise ratio becomes as written in Equation (5).

$$\text{SINR} = \frac{hPr_i^{-\alpha}}{I + \delta^2} = \frac{hPr_i^{-\alpha}}{I_{r_i}}. \tag{5}$$

$I_{r_i} = I + \delta^2$ is the cumulative interference from other BSs. I, the interference from other BSs and δ, the noise power, forms the interference plus noise received at the UE. The interference, I received at a UE in the HCN is the combination of the interfering power from the MBS of the first tier and the SBSs of the second tier. The interference now becomes as written in Equation (6).

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$$I = P_N g_N r_N^{-\alpha} + \sum_{j\epsilon J} P_j g_j r_j^{-\alpha}. \tag{6}$$

P_N and P_j are the transmit powers of the macro base station and SBSs, respectively. g_N and g_j represent the channel gain of the MBS and the jth SBS, respectively. r_N and r_j are the distances from the UE to the MBS and the jth SBS, respectively. J represents all interfering SBSs of the second tier.

3.2 | Coverage probability of the two-tier heterogeneous cellular network in strategic sleep mode

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 ($\min\{a_i r_i\}$) 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 as written in Equation (7).

$$P(a_i r_i < a_l r_l \forall l \neq i) = \int_{r=0}^{\infty} Z_i(r)\,(P(a_i r_i < a_l r_l \forall l \neq i))\,dr. \tag{7}$$

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

The user's activity in the HCN was used to determine the operating states of SBSs. Independent and identically random variables $G_i \sim G$ is assigned to all SBSs $j\,\epsilon\,\theta_j$. Where θ_j represents the set of available SBSs within the HCN and G has values in $[0, 1]$. G_i represents HCN user activity. Users within the HCN are active with probability g. SBSs with activity level x operate with probability $I(x)$ and are put to sleep with probability $1 - I(x)$. It is assumed that $I(x)$ is increasing, and thus active SBSs are distributed using the PPP written in Equation (8).

$$d_j E\{I\} = d_j \int_0^1 I(x) O_B(x) dx\,. \tag{8}$$

Let $g(x)$ be the condition that a cell is active because a user is active and Q_o be the arrangement of the SBSs to which the user connects. The UE's probability of using a link becomes as written in Equation (9).

$$P_{c,\text{stra}} = \frac{1}{E\{g\}} \int_0^1 x I_x P(\text{SINR} > \rho) O_B(x) dx. \tag{9}$$

Equation (10) is the strategic sleep mode coverage probability over all existing links in the HCN. The equation is based on the activity level of each tier $I(x)$ and the closeness of each base station of tier j to the UE. The first integral term of the coverage probability represents a user's ability to connect to the closest base station. The second integral term covers the probability of two events. The first event is that the nearby base station of the jth tier is either asleep or awake. The second event was the interferences from the remaining base stations.

$$P_{c,\text{stra}} = \frac{1}{E\{g\}} \int_0^1 \left\{ \begin{array}{c} x I_x P(Q_o = 1) P(\text{SINR} > \rho) \\ + \int_0^1 x(1 - I(x)) P(Q_o > 1) P(\text{SINR} > \rho) \end{array} \right\} O_B(x) dx \tag{10}$$

The coverage probability over all existing links is then split into the event that the user's closest SBS is awake and asleep, as shown in Equation (11).

$$P_{c,\text{stra}} = \frac{1}{E\{g\}} \int_0^1 \left\{ \begin{array}{c} x I_x \int_{r=0}^{\infty} exp\left(-\pi r^2 d_j E\{I\} P(\rho, \alpha)\right) exp\left(-\pi r^2 d_j\right) exp\left(\frac{-r^\alpha \rho \delta^2}{\beta P_j}\right) dr \\ + \int_0^1 x(1 - I(x)) P(Q_o > 1) P(\text{SINR} > \rho) \end{array} \right\} O_B(x) dx. \tag{11}$$

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3.3 | The sparse code multiple access (SCMA) SINR model

The signal from the transmitter has superimposed codewords (one SCMA block) and can be expressed as written in Equation (12):

$$Y_i = \text{diag}\,(g_i) \sum_{j=1}^{J} x_i + n = \text{diag}(g) X + n. \quad (12)$$

$X = \sum_{j=1}^{J} x_i$ are the superimposed codewords of J users at the transmitter and n is the additive white Gaussian noise with zero mean and variance σ^2. In SCMA, the codewords of J users are multiplexed on k subcarriers to form an SCMA block or code block. Power is shared among the J users in the code block. Each user's signal is detected at the receiver using a multi-user detection technique such as a message-passing algorithm (MPA). The general equation for the SINR of any UE in the SCMA-based HCN network is given by Equation (13):

$$\text{SINR}_i = \frac{P_i g_i}{J_i \left(N_o W + \sum_{j=1}^{J-1} P_i g_i^2 \right)}. \quad (13)$$

J_i is the number of layers assigned to a user in the SCMA code block.

3.3.1 | SCMA SINR for small cell users

Every subchannel $\left(b_j\right)$ allocated by BS j is occupied by two users with $g_{i,j}^{b_j} < g_{2,j}^{b_j}$. There are at least four SCMA layers in each SCMA code block. Therefore the SINR of two users within the coverage area of SBS j becomes as written in Equation (14) and modified in Equation (15).

$$\text{SINR}_{s1,j}^{\text{SM},b_j} = \frac{\left(1 - \lambda_j^{b_j}\right) P_j^{b_j} g_{1,j}^{b_j}}{J_1 . N_o b_j}. \quad (14)$$

$$\text{SINR}_{s2,j}^{\text{SM},b_j} = \frac{\lambda_j^{b_j} P_j^{b_j} g_{2,j}^{b_j}}{J_2 \left(N_o b_n + \left(1 - \lambda_j^{b_n}\right) P_j^{b_n} g_{1,j}^{b_n} \right)}. \quad (15)$$

J_1 and J_2 represent the number of SCMA layers assigned to UE_1 and UE_2. $\text{SINR}_{s1,j}^{\text{SM},b_j}$ and $\text{SINR}_{s2,j}^{\text{SM},b_j}$ are the signal-plus-interference-to-noise-ratios of UE_1 and UE_2 sharing the same sub-channel $b_j \in W_J$ in small cell j.

3.3.2 | SCMA SINR for macro cell users

Every subchannel b_n allocated by the MBS N is occupied by two users with $g_{i,N}^{b_n} < g_{2,N}^{b_n}$, therefore the SINR of the two users within the coverage of the MBS N becomes as written in Equation (16) and modified in Equation (17).

$$SINR_{s1,N}^{\text{SM},b_n} = \frac{\left(1 - \lambda_N^{b_n}\right) P_N^{b_n} g_{1,N}^{b_n}}{J_1 N_o b_N}. \quad (16)$$

$$\text{SINR}_{s2,N}^{\text{SM},b_n} = \frac{\lambda_N^{b_n} P_N^{b_n} g_{2,N}^{b_n}}{J_2 \left(N_o b_n + \left(1 - \lambda_N^{b_n}\right) P_N^{b_n} g_{1,N}^{b_n} \right)}, \quad (17)$$

where $\text{SINR}_{s1,N}^{\text{SM},b_n}$ and $\text{SINR}_{s2,N}^{\text{SM},b_n}$ are the signal-plus-interference-to-noise ratios of UE_1 and UE_2 sharing the same sub-channel $b_n \in W_N$ in macrocell N.

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3.4 | Sum rate for small cell and macro cell users

The total bandwidth of the system is represented by B, which is divided to get subcarriers of bandwidth b. The total number of channels in the HCN becomes, B/b. Therefore the total number of system channels $W = \{b_{1,}b_2, b_3, \dots, b_4, \dots B/b\}$. Let W_J represent the channels used in the small cell tier and W_N represent the channels used in the macro cell tier, such that, $\{W_J, W_n \in W\}$ and $W_J \cup W_n = W$. It eliminates cross-tier interference between the small and macro cell tiers. It is assumed that $W_J \cap W_N = \emptyset$ and $W_J, W_N \neq \emptyset$.

Therefore, the coverage and network throughput depend on the subcarriers utilized within the small and macro cell tiers. The sum rate is the throughput on any channel b_n, $n \in \{1, 2, 3 \dots, B/b\}$. The sum rate is expressed as written in Equation (18).

$$R_{b_n} = P_c Log(1 + \rho). \tag{18}$$

R_{b_n} is the throughput on channel n. P_c is the coverage probability and ρ is the signal-plus-interference-to-noise-ratio. The throughput of the small cell tier (R_J) becomes as written in Equation (19).

$$R_J = d_j \sum b_j \in W_J R_{b_j} . \tag{19}$$

For random sleep mode, the throughput of the small cell tier is modified as written in Equation (20a).

$$R_J = d_j \left(|W_J| \, P_{c,ran} Log \left(1 + \rho_j\right)\right) . \tag{20a}$$

For strategic sleep mode, the throughput of the small cell tier is modified as written in Equation (20b).

$$R_J = d_{\mathrm{j}} \left(|W_J| \, P_{\mathrm{c,stra}} Log \left(1 + \rho_j\right)\right) , \tag{20b}$$

where ρ_j is the SINR threshold of the small cell tier. R_J is the combined throughput of all small cells. R_{b_j} is the throughput of one small cell channel.

The throughput of the macro cell tier becomes as written in Equation (21).

$$R_N = d_N \sum b_n \in W_N R_{b_n} \quad . \tag{21}$$

The BS of the macro cell tier is never put to sleep. Therefore, Equation (21) is rewritten, as shown in Equation (22).

$$R_N = d_N \left(|W_N| \, P_c Log\left(1 + \rho_N\right)\right) , \tag{22}$$

where ρ_N is the SINR threshold of the macro cell. R_N is the throughput of the macro cell. R_{b_n} is the throughput of one macro cell channel.

The total throughput (R_T) of the HCN network model becomes as written in Equation (23):

$$R_T = R_N + R_J. \tag{23}$$

3.5 | The energy-spectral-efficiency (ESE) of SCMA based HCN

The SE of the SCMA-based HCN is given, as shown in Equation (24).

$$\mathrm{SE}_{\mathrm{SM}} = \frac{R_T^{\mathrm{SM}}}{W}, \tag{24}$$

where R_T^{SM} is the throughput of the two-tier HCN when SCMA is used as the multiple access technique.

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3.5.1 | The small base station strategic sleeping strategy

The SBSs in the HCN can be put to sleep based on mobile traffic demands and mobile user activity. The mode of putting SBS to sleep considered in this study is strategic sleep. 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:

$$C_S = d_j E\{I\} \left(P_{s,j} + \Delta_j \beta P_j\right) + d_j(1 - E\{I\})P_{\text{sleep}}. \tag{25}$$

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.

$$E\{I\} = \int_0^1 I(x)O_B(x)dx. \tag{26}$$

B represents the random activity of mobile users within the HCN and takes values in $[0, 1]$. $O_B(x)$ is the PDF of B. The strategic sleep mode models traffic for the entire twenty-four-hour day duration. The strategic sleep mode is adaptive to mobile traffic's temporal and spatial variation within the day.

The EE of the SCMA-based HCN for strategic sleep mode is given as shown in Equation (27).

$$EE_{\text{stra}}^{\text{SM}} = \frac{R_T^{\text{SM}}}{\left[d_j E\{I\} \left(P_{s,j} + \Delta_j \beta P_j\right) + d_j(1 - E\{I\})P_{\text{sleep}}\right] + \left(P_{s,N} + \beta \Delta_N P_N\right)}, \tag{27}$$

where $P_{s,j}$ is the power consumed by the circuitry of the SBS, $P_{s,N}$ is the power by the circuitry of the MBS, P_j is the transmit power of the SBS, P_N is the transmit power of the MBS, β is a scaling factor, Δ_j is the slope of the load-dependent power consumption of the SBS, and Δ_N is the slope of the load-dependent power consumption of the MBS.

3.6 | The ESE optimization problem

HCNs can increase the throughput of a mobile communication system by deploying many low-power base stations. However, higher throughput in an HCN comes at an energy cost that requires simultaneous adjusting of the network's energy and spectrum efficiency to find an optimal solution. The goal would be to maximize the energy and spectrum efficiency of all UE minimum data rates and the network's maximum transmit power using SCMA. The maximization of EE and spectral efficiency (EE) is subject to four constraints. The first constraint ($C1$) ensures that all links of users connected to any SBS meet at least the minimum required SINR threshold $\left(\rho_{\text{required}}\right)$. The second constraint ($C2$) ensures that all links of users connected to the MBS meet at least the minimum required SINR threshold $\left(\rho_{\text{required}}\right)$. The third constraint ($C3$)ensures that the total of power utilized by the small cell BSs in the HCN must not exceed the maximum power $\left(P_{\max}^J\right)$ of all SBSs combined should utilize. The fourth ($C4$) constraint ensures that the density of SBS $\left(d_j\right)$ in the HCN does not fall below the set minimum or above the maximum allowable limit.

$$\textit{Maximize}$$

$$EE = \zeta_{EE}, \tag{28}$$

$$\textit{Maximize}$$

$$\text{SE} = \zeta_{\text{SE}}, \tag{29}$$

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$$\text{Subject to}:$$

$$C1: \rho_{i,j} \geq \rho_{\text{required}},$$

$$C2: \rho_{i,n} \geq \rho_{\text{required},}$$

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

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

$P^J_{\max}$ - The maximum transmit power of SBS.
d_j - Density of SBS.
EE, SE - Energy efficiency and spectral efficiency, respectively.
ρ_{required} - The SINR threshold for SBS User Equipment 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.
ζ_{EE} - The HCN EE using a selected multiple access technique.
ζ_{SE} - The HCN SE using a selected multiple access technique.

The multiobjective ESE optimization problem of the two-tier NOMA-based HCN was converted into a single objective optimization problem and solved using a weighted-sum modified PSO technique. The PSO algorithm was developed and used to simultaneously maximize the spectral and EE of the two-tier HCN.

The optimization problem was converted to a minimization problem through an algebraic process as:

$$\textit{Minimize}$$

$$EE = -(\zeta_{EE}), \tag{30}$$

$$\textit{Minimize}$$

$$\text{SE} = -(\zeta_{\text{SE}}), \tag{31}$$

$$\text{Subject to}:$$

$$C1: \rho_{i,j} \geq \rho_{\text{required}},$$

$$C2: \rho_{i,n} \geq \rho_{\text{required},}$$

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

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

The multiobjective optimization problem is converted into a single objective problem using the weighted sum approach as:

$$\textit{Minimize}$$

$$\text{ESE} = W_1(-(\zeta_{\text{SE}})) + W_2(-(\zeta_{EE})), \tag{32}$$

$$\text{Subject to}:$$

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$$\text{C1} : \rho_{\text{i,j}} \geq \rho_{\text{required}},$$

$$\text{C2} : \rho_{\text{i,n}} \geq \rho_{\text{required}},$$

$$\text{C3} : \sum_{\text{j}=1}^{\text{J}} \sum_{\text{i}=1}^{\text{I}} \beta P_{\text{i,j}} \leq \sum_{\text{j}=\text{i}}^{\text{J}} \text{P}_{\text{max}}^{\text{J}},$$

$$\text{C4} : \text{d}_{\text{j,min}} \leq \text{d}_{\text{j}} \leq \text{d}_{\text{j,max}}.$$

The single objective optimization problem was solved with a weighted sum modified PSO algorithm. The PSO technique implements Algorithm 1 to simultaneously maximize the SE and EE of an SCMA-based HCN.

Algorithm 1. : The weighted sum modified particle swarm optimization algorithm

Input: Average power consumption (C), coverage probability (P_c), n_1, n_2, m_1, x (population size), number of iterations (J), $Z_{k,\min}$, $Z_{k,\max}$, W_1, W_2, network simulation parameters.
Output: Pareto-optimal front for energy and SE maximization.
Initialization:
Set dynamic weights W_1 and W_2 to zero.
Set initial positions of optimization parameter Z_k as:
$Z_{k,i} = Z_{k,\min} + \left(Z_{k,\max} - Z_{k,\min}\right) V_k$, where $i = 1, 2, \ldots, x$.
Set initial velocity $S_{k,i} = 0$
Set V_k as a uniformly distributed random number between 0 and 1
While $j \leq J$ (*number of iterations*) **do**
Compute:
$I_{k,i} = C\left(Z_{k,i}\right)$, where $i = 1, 2, \ldots, x$
Determine:
$I_{\text{optimum}_{k,i}} = I_{k,i}$; $A_{\text{optimum}_k} = \text{minimum}\left(I_{\text{optimum}_{k,i}}\right)$
Note the location of I_{bki} and A_{kb}
Update the dynamic weights as:
$W_1 = \left|\frac{2\pi k}{150}\right|$; $W_2 = 1 - W_1$
Update the velocity as:
$S_{k+1,i} = m_1 S_{k,i} + n_1\left(I_{bki} - Z_{k,i}\right) V_k + n_2\left(A_{kb} - Z_{k,i}\right) V_k$
Update the position Z_k as:
$Z_{k+1,i} = Z_{k,i} + S_{k+1,i}$
Fit values of initial positions Z_k into the Equation (32)
Compute new fitness:
$I_{k+1,i} = C\left(Z_{k+1,i}\right)$
if $I_{k+1,i} < I_{\text{optimum}_{k,i}}$ **then**
$I_{\text{optimum}_{k+1,i}} = I_{k+1,i}$
else
$I_{\text{optimum}_{k+1,i}} = I_{k,i}$
Compute
$A_{\text{optimum}_{k+1}} = \text{minimum}\left(I_{\text{optimum}_{k+1,i}}\right)$
end
end

The single objective optimization problem was solved with a weighted-sum modified PSO algorithm. The weighted-sum modified PSO technique implements the following steps to find optimal solutions:

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a. The network simulation parameters are first initialized using Table 1. The coverage probability $\left(P_{c,\text{stra}}\right)$ and average power consumption (C) are computed.
b. The objective function or the single objective optimization problem (SOP) is created with all constraints placed appropriately within the problem.
c. The upper bound and lower bound of the constraints are set.
d. The optimization parameters are all initialized. The dynamic weights W_1 and W_2 are set to zero. The population size (x) is set along with the initial position of the optimization parameter (Z_k) and the maximum iteration (J).
e. The goal is to get the optimum group values of SE and EE $\left(A_{\text{optimum}}\right)$the individual and the values of the various parameters SBS density and transmit power $\left(I_{\text{optimum}}\right)$ that achieves the group's optimum values.
f. The initial position of the ith individual in the population is given as:

$$Z_{k,i} = Z_{k,\min} + \left(Z_{k,\max} - Z_{k,\min}\right) V_k \tag{33}$$

$Z_{k,\max}$ and $Z_{k,\min}$ are the bounds of the variable Z_k, V_k is a random number uniformly distributed between 0 and 1, and k represents the iteration number.
g. The fitness of the ith individual is computed as:

$$I_{k,i} = C\left(Z_{k,i}\right). \tag{34}$$

h. The best fitness of each individual is I_i and it is given as:

$$I_{\text{optimum}_{k,i}} = I_{k,i}. \tag{35}$$

i. The group fitness is calculated as:

$$A_{\text{optimum}_k} = \text{minimum}\left(I_{\text{optimum}_{k,i}}\right). \tag{36}$$

j. The location of I_{optimum} and A_{optimum} are noted as I_{bki} and A_{kb}.
k. The dynamic weights, W_1 and W_2 in Equation (32), combine the original multiobjective optimization problem into a single optimization problem. These dynamic weights were used to modify the PSO algorithm and updated according to the following equations $W_1 = \left|\frac{2\pi k}{150}\right|$; $W_2 = 1 - W_1$.
l. The velocity of the individual is updated using the equation:

$$S_{k+1,i} = m_1 S_{k,i} + n_1\left(I_{bki} - Z_{k,i}\right) V_k + n_2\left(A_{kb} - Z_{k,i}\right) V_k. \tag{37}$$

$S_{k,i}$ is the initial velocity of the individual, m_1, n_1, n_2 are tuning parameters.
m. The position of each individual is updated using:

$$Z_{k+1} = Z_{k,\min} + \left(Z_{k,\max} - Z_{k,\min}\right) V_k. \tag{38}$$

n. The new fitness of the ith individual is computed as:

$$I_{k+1,i} = C\left(Z_{k+1,i}\right). \tag{39}$$

o. When the new fitness is lower than $I_{\text{optimum}_{k,i}}$, it replaces it. Thus, the new global fitness becomes:

$$A_{\text{optimum}_{k+1}} = \text{minimum}\left(I_{\text{optimum}_{k+1,i}}\right) \tag{40}$$

p. The algorithm continues to run until the maximum number of iterations (J) is exceeded.
q. The output is obtained as a graph of the Pareto optimal front containing the non-dominated solutions of the ESE optimization problem.

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4 | NUMERICAL RESULTS AND DISCUSSION

The optimization of the SE and EE of the two-tier HCN is evaluated through numerical simulations in MATLAB2018b. The obtained results are thoroughly discussed. The performance of the genetic algorithm (GA) available in MATLAB2018b for multiobjective optimization is compared with the proposed weighted sum modified PSO algorithm. The simulation parameters as obtained from References 5,25 are presented in Table 2.

The energy and SE optimization of the SCMA-based HCN at various traffic levels were simulated using Algorithm 1. The result shown in Figure 2 is the Pareto-optimal front for the strategic sleep mode and at low traffic levels using the proposed weighted sum modified PSO algorithm. The Pareto-optimal front is convex. The inverse relationship for strategic sleep mode at low traffic levels is due to UEs preferring to connect to the MBS instead of nearby SBSs. The network operator may encourage connection to nearby SBSs by increasing the transmit power of the SBS, resulting in an improvement in SE and a decline in EE. Table 3 shows that at low traffic levels and in strategic sleep mode, the proposed PSO algorithm favors lower SBS density and SBS power values than it does at high traffic levels. The EE and SE achieved at high traffic are more significant than the SE and EE attainable at low traffic levels due to the higher SBS density and SBS power favored by the proposed PSO algorithm at high traffic levels and in strategic sleep mode. The proposed PSO algorithm was compared with GA at low traffic levels. As seen in Figure 3 for GA, the Pareto optimal front also shows an inverse relationship between SE and EE. The negative values of SE on the y-axis and EE on the x-axis seen in Figure 3 for GA at low traffic levels are due to the minimization objective shown in Equations (30) and (31). Although both algorithms generated similar optimal values of SE and EE, the proposed PSO algorithm achieved the optimal SE and EE with a 37.56% lower SBS density and a 53.04% lower SBS transmit power.

In Figures 4 and 5, the Pareto-optimal front achieved using the proposed PSO algorithm, and GA at high traffic levels are both non-convex, showing the simultaneous maximization of the SE and EE. The proposed PSO algorithm achieved the optimal SE and EE at high traffic levels with nearly the same SBS density and SBS transmit power as the GA. Figure 6 shows the unoptimized tradeoff between EE and SE for SCMA-based HCN in strategic sleep mode. When the transmit power of the MBS is varied, the full range of values for the tradeoff between EE and SE can be seen from the point where

TABLE 2 Simulation parameters

Parameter	Value
MBS transmit power (βP_N)	31 W
SBS transmit power $\left(\beta P_j\right)$	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 (α)	4
SBS sleep mode power consumption $\left(P_{\text{sleep}}\right)$	2.9 W
Number of channels allocated to MBS	6
Number of channels allocated to SBS	4
SBS density $\left(d_j\right)$	Variable
MBS density (d_N)	$10^{-1}/\text{m}^2$
SINR threshold of small cell $\left(\rho_j\right)$	Variable
The slope of load-dependent power consumption of SBS $\left(\Delta_j\right)$	4.7
The slope of load-dependent power consumption of MBS (Δ_N)	8.0
Population size (x)	150
Antenna pattern	Omnidirectional
Network input-output model	Single-input-single-output (SISO)

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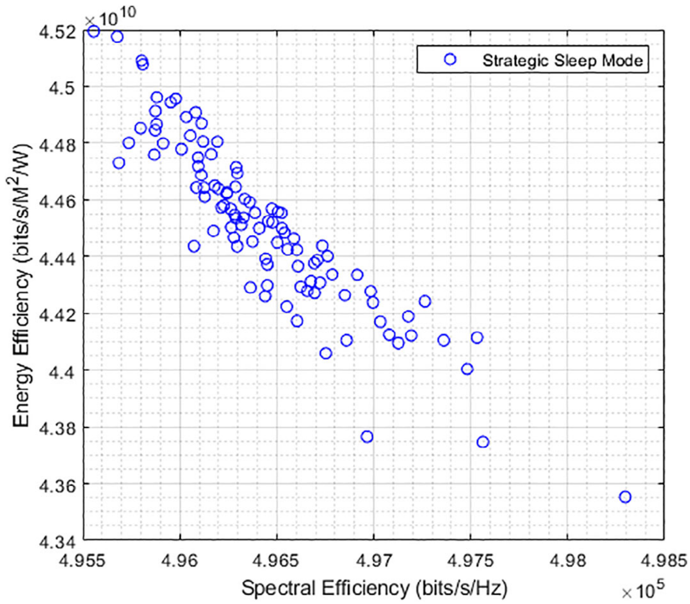

FIGURE 2 ESE optimization of SCMA-based HCN using proposed PSO algorithm at low traffic levels

TABLE 3 Comparison of ESE optimization solutions of proposed PSO algorithm with genetic algorithm (GA) at Low, moderate, and high traffic levels

Constraints

SBS transmit power $(\beta P_j) = 0\text{-}1$ W

Traffic level = *Moderate*: 0.3-0.7

SBS density $(d_j) = 0.01\text{-}0.09$ (m^{-2})

MBS density $(d_N) = 10^{-2}$ (m^{-2})

SINR threshold $(\rho) = 3\text{-}9$ for a moderate traffic case

Comparison of optimized solutions

	SBS density (m^{-2})	SBS transmit power (W)	Spectral efficiency (bps/Hz)	Energy efficiency bits/s/m^2/W
Proposed weighted sum modified PSO algorithm at low traffic levels	0.0128	0.3737	4.9641×10^5	4.5176×10^{10}
Genetic algorithm (GA) at low traffic levels	0.0205	0.7957	4.9025×10^5	4.4632×10^{10}
Proposed weighted sum modified PSO algorithm at moderate traffic levels	0.0054	0.5088	8.7425×10^4	8.2522×10^9
Genetic algorithm (GA) at moderate traffic levels	0.0082	0.6918	8.9499×10^4	8.2548×10^9
Proposed weighted sum modified PSO algorithm at high traffic levels	0.0880	0.9932	1.6443×10^6	1.2800×10^{11}
Genetic algorithm (GA) at high traffic levels	0.0900	1.0000	1.7726×10^6	1.3970×10^{11}

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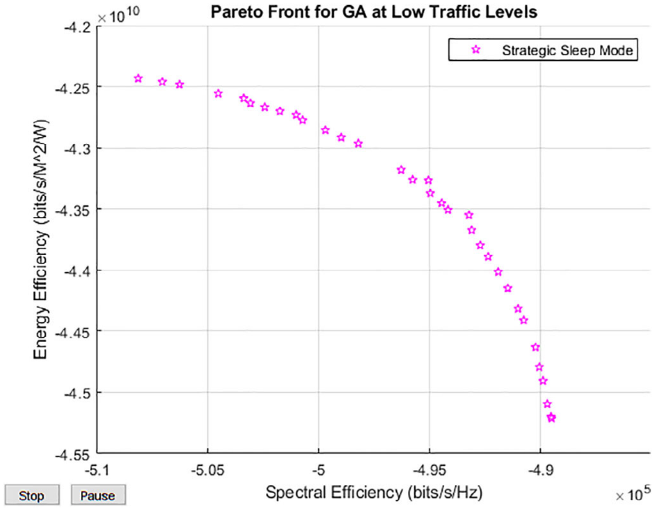

FIGURE 3 ESE optimization of SCMA-based HCN using genetic algorithm (GA) at low traffic levels

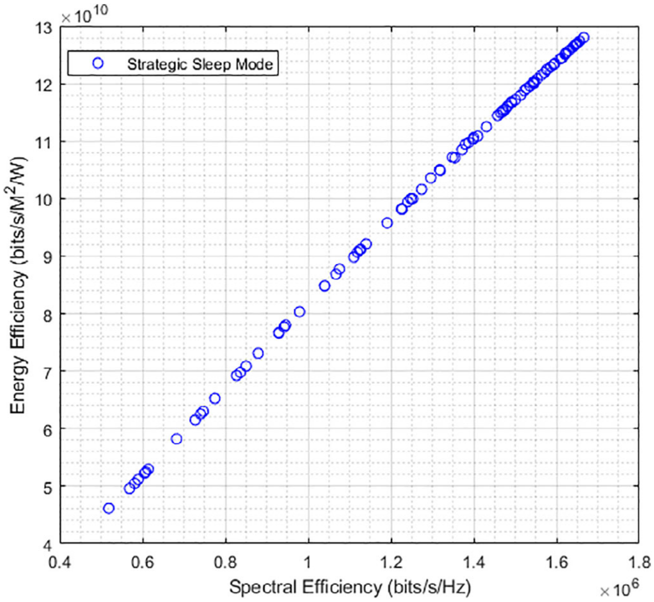

FIGURE 4 ESE optimization of SCMA-based HCN using proposed PSO algorithm at high traffic levels

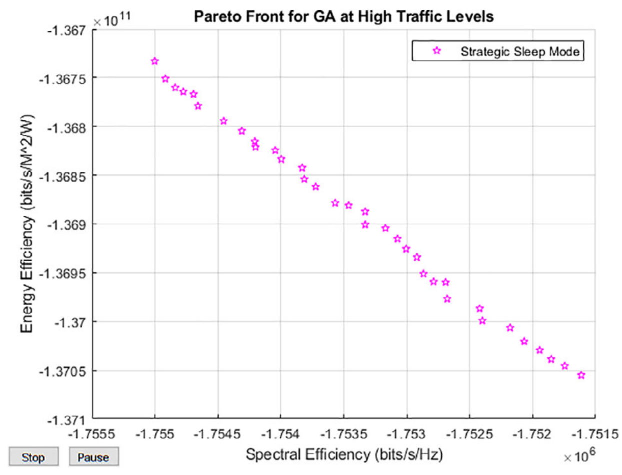

FIGURE 5 ESE optimization of SCMA-based HCN using genetic algorithm (GA) at high traffic levels

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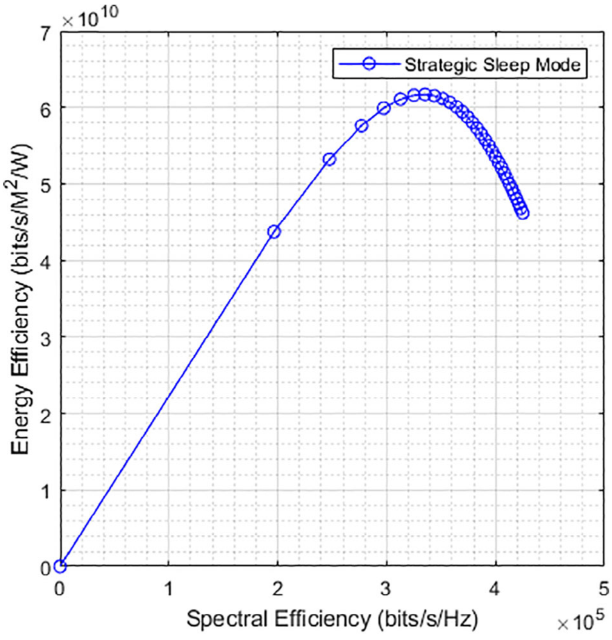

FIGURE 6 Unoptimized ESE of SCMA-based HCN

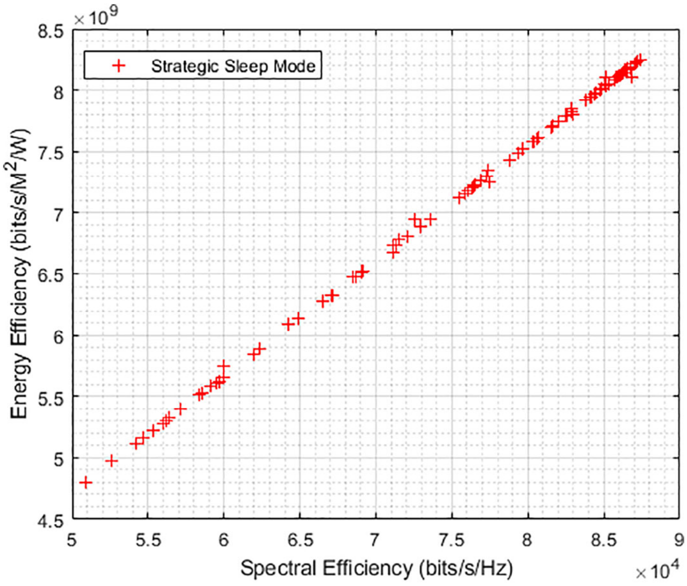

FIGURE 7 ESE optimization of SCMA-based HCN using proposed PSO algorithm at moderate traffic levels

all base stations, including the MBS, are shut off, at the origin (the point where SE and EE are zero). The EE rises almost linearly with the SE until the EE reaches its maximum value at 6.2×10^{10} bits/s/m^2/W. Beyond the maximum value for EE, the tradeoff between EE and SE becomes noticeable. The SE continues to increase till it reaches its maximum value at 3.3×10^5 bps/Hz, but at the cost of a 22% drop in EE. 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 SE outlook maintains the profile that the network provider can support. The unoptimized result for ESE optimization in strategic sleep mode shows a much lower level of SE and EE. Compared to the proposed PSO optimized SCMA-based HCN, the unoptimized HCN has an 80% lower SE and a 51% lower EE.

The proposed PSO algorithm was compared with GA at moderate traffic levels. The ESE optimization constraints were varied within the range specified in Table 1. The Pareto optimal front, as seen in Figures 7 and 8 for the proposed

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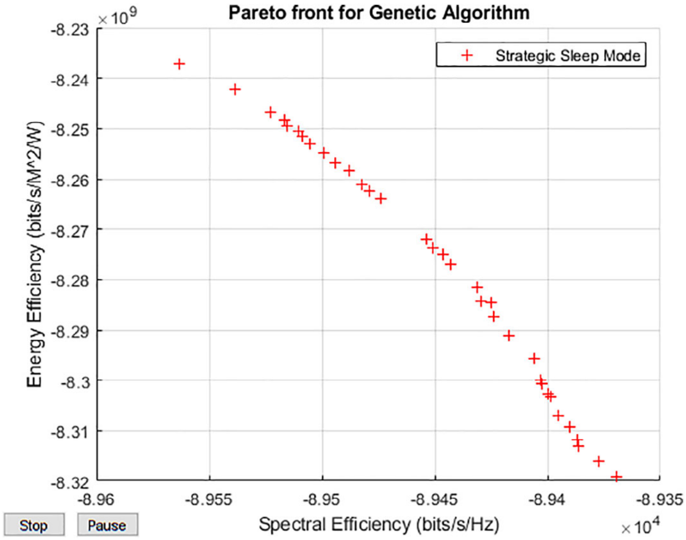

FIGURE 8 ESE optimization of SCMA-based HCN using genetic algorithm (GA) at moderate traffic levels

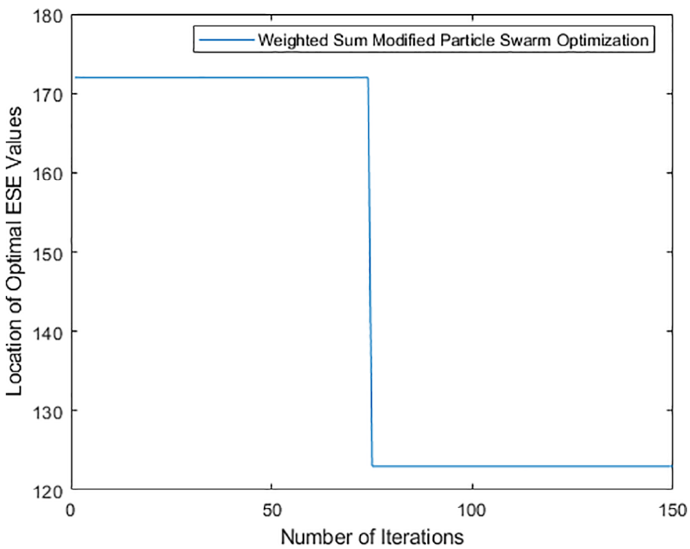

FIGURE 9 Convergence analysis for proposed weighted sum modified particle swarm optimization algorithm

PSO algorithm and GA, respectively, are non-convex, showing the simultaneous maximization of the SE and EE of the SCMA-based HCN at moderate traffic levels. The two algorithms generated similar optimal values of SE and EE. Still, the PSO algorithm achieved the optimal SE and EE with a 51.85% lower SBS density and a 35.96% lower SBS transmit power.

The proposed weighted sum modified PSO algorithm has two parts in its complexity. The first part is the modified PSO process with a complexity of $O(XD)$. Where X is the population size, and D represents the dimensionality. The second part of the algorithm involves implementing the SCMA technique, which has a complexity of $O(n)$, where n represents the number of UE signals in an SCMA code block. The value of $n = 2$ in this article. The complexity of the entire algorithm is computed as $O(XD) + O(n) = O(XD)$. The time complexity of the algorithm is 32 s on average.

The convergence behavior of the proposed ESE optimization algorithm is shown in Figure 9. Figure 7 shows the number of iterations the proposed PSO algorithm takes to find the optimum solution to the ESE maximization problem. The location of the ESE maximization problem was found to be at position 123 for an instance of running the algorithm at moderate traffic levels. The algorithm stops running after 150 iterations, although it reaches a stable value after 75 iterations.

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The result of this research study answered the question of the numerical implication of optimizing the ESE of a sleep-mode enabled SCMA-based HCN on the density and transmit power of randomly deployed SBSs at various network traffic levels.

The proposed weighted sum PSO has a convergence time that satisfactorily optimizes all the network variables. Compared to the weighted sum modified PSO algorithm, the GA converges too quickly (after 20 iterations) and does not satisfactorily optimize some network variables like the SBS's transmit power and density.

5 | CONCLUSION

This research study set out to gain insight into the effect of stochastic deployment of SBSs on the SE and EE on sleep-mode enabled SCMA-based HCNs. The result obtained showed that the SBS density and SBS transmit power affect the SE and EE of SCMA-based HCNs. The sleep mode technique employed affected the choice of SBS density, and SBS transmit power.

This research study assumed that all installed SBSs are controlled only by the network operator. This assumption may not practically be the case, especially for indoor applications. The practical implementation to check the real-life implication of the proposed traffic-aware optimization algorithm on network operators' operating expenses (OPEX) was not carried out. The instantaneous channel state information was not considered as the research assumed perfect channel state information at all base stations.

The following are some recommendations for further studies:

1. The traffic-aware optimization algorithm may be further refined for implementation on actual base stations.
2. Higher tier orders of HCNs may be considered where the deployed SBSs are not under the direct control of the network operator.

CONFLICT OF INTEREST

The authors declare no potential conflict of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available in IEEEXplore at https://ieeexplore.ieee.org/document/6502479, reference number 6502479.

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