Smart 5G Small Cell Mobile Networking with Sleep Strategy Using Novel Swarm Optimization

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***Abstract*—Due to its major contribution to the overall energy consumption in Information and Communication Technologies (ICT), lowering the energy consumption of mobile communication networks has attracted a lot of attention. This study presents the implementation of a 5G network model based on heterogeneity, employing macro cells and small cells, in conjunction with diverse users and control techniques. In this work, the analysis is performed between the consumption of energy and the performance of users in the cellular networks. The objective is to address the identified problem which is related to energy conservation and proposed a solution utilizing the Modified Particle Swarm Optimization (MPSO) algorithm, which is then compared with the existing Iterative Optimization Algorithm (IOA). The sleep strategy involved in this work helps to save energy by overlapping the cells. The evaluation of the implemented solution focuses on various parameters, including contract rate, power, earnings, and energy efficiency. Comparing the outcomes achieved through the two optimization algorithms, the MPSO-based evaluation demonstrates superior performance over the iterative optimization algorithm in terms of energy efficiency and power consumption. Before applying sleep strategy, the energy efficiency is 2.6%, after applying sleep strategy with IOA having 4% and with suggested approach efficiency is obtained is 6%. The evaluation is conducted using the Matlab software tool.**

***Keywords*—5G technology, base station, sleep strategy, Modified Particle Swarm Optimization (MPSO)**

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I. Introduction

Given the anticipated surge in traffic, developing of small cell networks has become an imperative result for 5G cellular networks [1]. Advanced techniques such as Massive Multiple Input Multiple Output (MIMO) and millimeter wave enhance transmission rates and reduce power consumption in 5G mobile networks [2, 3]. However, the predicted increase in traffic at small cell Base Stations (BS) necessitates greater processing power. Thus, achieving energy efficiency in 5G small cell networks requires carefully examining the tradeoff between processing and transmission power. Extensive research on this topic has been conducted [4, 5].

In conventional energy efficiency evaluations of BSs, computation power has often been considered a constant, with less emphasis on it than transmission power [6]. Consequently, energy efficiency studies in small cell networks have primarily focused on optimizing the power transmitted near the base stations [7]. Additionally, base station sleeps modes have been explored to improve energy efficiency. These modes involve turning off Radio Frequency (RF) chains and emitters during transmission to conserve power [8]. Moreover, the adoption of massive MIMO and millimeter wave technologies has increased the computational demands and complexity of signal processing in small-cell BSs [9, 10]. Despite the smaller power needs for transmission in small cell BSs, there are situations in 5G cellular networks with ultra-dense deployment of small cell BSs where the computing power of BSs exceeds their transmission power [11]. Extensive

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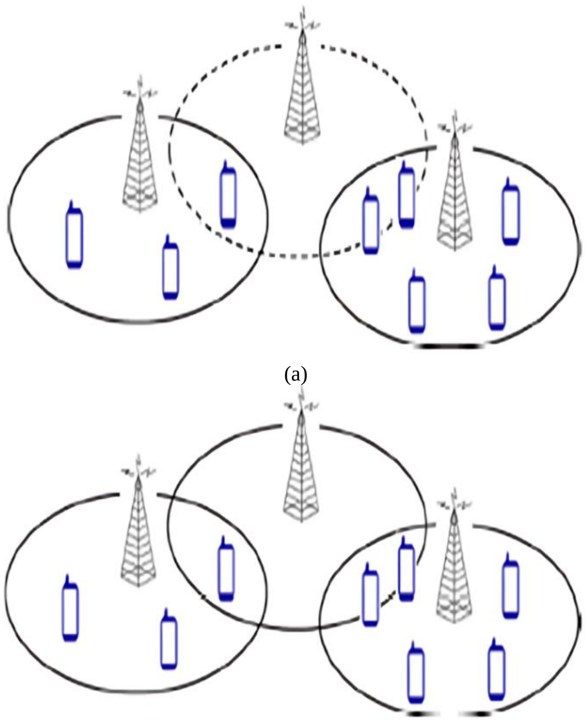
research has been conducted to explore energy-saving techniques, one among the techniques is utilization of sleep modes for reducing energy consumption in mobile communication networks.

Fig. 1 further illustrates that switching off the BS can yield additional energy savings when a BS experiences minimal traffic and neighboring BSs can handle the workload.



(a)

(b)

Fig. 1. Function of base stations (a) activation; (b) deactivation [9].

In recent years, soft computing techniques have emerged as powerful tools for addressing real-world problems characterized by uncertainty, imprecision, and complexity. Unlike traditional computing approaches that rely on precise logic and mathematical models, soft-computing techniques offer approximate solutions that effectively handle uncertain and incomplete data. Due to their merits, these techniques have been widely applied to various engineering problems [12–16]. This paper presents a heterogeneous-based 5G network model incorporating macro and small cells, data, and control planes. Generally, power consumption at base stations is regulated by a sleep strategy. This study suggests employing a Particle Swarm Optimization (PSO) technique to increase the network system's effectiveness and maximize the sum of the tiny cell users' revenues. The effectiveness of the adopted strategy for power control and sleep strategy is demonstrated by simulation results. Following is a sufficient summary of the main contributions of this paper, which were inspired by the methodology in [17].

- It introduces a combined energy-saving scheme incorporating a sleep strategy and an optimization technique to control power allocation, which results in enhanced energy savings.
- We are implementing a random sleep strategy with three crucial conditions. The optimization technique aims to satisfy these conditions while maximizing power savings.

It is recommended to employ a distributed power control strategy to reduce the algorithm's complexity and minimize the need for message exchange.

The rest of the paper is organized as follows. A description of random and dynamic sleep techniques is included in Section II. The PSO algorithm and the system model are elaborated in Sections III and IV, respectively. A detailed analysis of the simulation results is provided in Section V. Lastly, Section VI concludes the work, highlighting the key findings.

II. Literature Review

In literature, the study concentrates on the optimization of energy efficiency. Zhang *et al.* [18] designed an Orthogonal Frequency Division Multiple Access (OFDMA). The author designed a heterogeneous model for optimization of small cell base station. The quality of service, allocation of power, energy efficiency is evaluated. In this generation the 5G small cell base stations are necessary to provide higher rate of data, effectiveness in cost and lower latency. Due to the utilization of large quantity of 5G small cell base stations have a new difficulty in terms of energy efficiency. To overcome this problem Hawasli and Çolak [19] utilized a sleep strategy. Three algorithms were proposed by author for operating the small cell base station.

Ge *et al.* [20] suggested Landauer principle by which the consumption of power is optimized in 5G small cell base station to achieve the energy efficiency. Valenzuela-Valdes *et al.* [21] suggested a network with super dense small cells. By deploying dense small cells, the service in providing data in networks can be improved and speed can be ranged above 1Gbps. Wang *et al.* [22] utilized OFDMA scheme for balancing the efficiency of energy and bandwidth in base station with small cells. The author utilized game theoretic approach to distribute a bandwidth sharing technology for networks with smart 5G small cells. For deployment in 5G networks with the highest possible energy efficiency, small cells are a feasible option.

Venkateswararao and Swain [23] suggested sleep strategy model in ultra dense small cell BS. The energy efficiency is improved by transferring the traffic load of one small cell to other small cell which is said to be distribution of data based on the load. By utilizing this method, the state of environmental condition can be maintained in ultra dense networks. Yang *et al.* [24] suggested semi-Markov process-based methodology for spatiotemporal mobility prediction together with steady state and gain analysis in cellular networks.

Huang *et al.* [25] introduced Femtocell in heterogeneous 5G cellular networks. The author also utilized sleep strategy to manage the traffic load and utilized Markov-based prediction methodology.

In order to implement PBL with Knowledge Graph (KG)-based guidance for practical labs in cybersecurity training, Deng *et al.* [26] created an online laboratory environment. With KG's instruction, learners may access a virtual lab environment that simulates real-world cybersecurity issues. A deep learning-based dynamic network anomaly detection system. Lin *et al.* [27] designed a deep neural network model with Long Short Term Memory (LSTM) and then add an Attention Mechanism (AM) to improve the accuracy of the model. The new era of computer networks using machine learning algorithms is focused by Namasudra *et al.* [28]. Runad *et al.* [29] utilized a framework called Subspace Clustering using Evolutionary algorithm, Off-Spring Generation and Multi-Objective Optimization (SCEOMOO) to find the optimal subspace clusters. This algorithm can be used in the suggested model to achieve good range of optimum results. Namasudra *et al.* [30] suggested a new access control model namely Profile Based Access Control Model (PrBAC) for cloud computing.

However, no research on the basis of energy efficiency in 5G small cell BSs by taking sleeping strategy with optimization approach into consideration has been documented in the literature. Therefore, we examine the energy efficiency of macro base stations and small cell BSs in this paper by considering sleeping method and swarm optimization approach. The suggested paradigm is anticipated to be considered in 5G small cell BSs, macro cell BSs, and beyond. Even while the aforementioned literature provided a variety of sleep techniques, they failed to take control over the consumption of power and the management of interference into account in addition to optimization and sleep strategy approach.

TABLE I. ENERGY EFFICIENCY METHODS

Reference	Network model	Methodology	Findings
Zhang *et al*. [18]	Heterogeneous small cell n/w	wireless backhaul bandwidth allocation in orthogonal frequency division multiple	the QoS requirement of small cell users increases, the more power is required to meet the higher QoS requirement.
Hawasli *et al*. [19]	5G Heterogeneous small cell n/w	Power optimization using load balancing technique	the HetNet can save about 20% power daily
Ge *et al.* [20]	5G small cell n/w	computation power based on the Landauer principle	The computation power of a 5G small cell BS can approach 800 W when massive MIMO (e.g., 128 antennas) is deployed to transmit high volume traffic.
Valenzuela-Valdes *et al*. [21]	Ultra Dense small cell n/w	The use of super dense heterogeneous networks is one of the most promising alternatives to provide services with speeds above 1 Gbps.	The network performance has been measured in terms of Capacity, Signal to Interference plus Noise Ratio, and Energy Consumption.
Wang *et al*. [26]	5G wireless n/w	a game theoretic approach to design a distributed energy efficient bandwidth sharing mechanism for small-cell networks.	solution relies on dynamically learning good strategies for the user-equipment association
Venkateswararo *et al.* [23]	5G ultra dense n/w	An efficient cell modeling (ECM) algorithm for small cell formation, and binary particle swarm optimization-based small cell deployment (BPSD) to optimize the deployment of small base stations	Proposed approaches improve the energy efficiency and connectivity in the ultra-dense small cell network.
Yang *et al*. [24]	5G cellular n/w	hysteretic BS sleeping strategy in 5G cellular network.	Numerical results show that the longer transition delay is, the worse system performance the BS is suffered
Huang *et al*. [25]	Dynamic Femto cell 5G n/w	the proposed DFOO strategies consider the operation of base stations (BSs) according to the predicted time-varying traffic load from Markov procedure.	proposed DFOO algorithm provide considerable improvement of NEE while ensuring the load balancing of the HCN.

III. EXPERIMENT AND METHOD

A. Sleep Strategy

The sleep strategy can be categorized into two types: random sleeping and strategic sleep, as described in [13]. This study analyzes the optimization of power consumption at the Macro Cell Base Station (MBS) by employing a specific type of sleep strategy. The dynamic investigation of switching off the MBS is conducted to evaluate the power consumption associated with the MBS in sleep mode.

1) Random sleep strategy

A Bernoulli trail approach represents the random sleeping sleep strategy [31]. In this approach, each base station has an operating probability, denoted as "q" and the probability of being in sleep mode is represented as "1–q". Fig. 2 illustrates this concept. By implementing random sleeping at the macro layer, the average power consumption in the macro cell networks can be reduced to some extent.

2) Dynamic sleep strategy

Rather than randomly turning off macro base stations (MBSs), an alternative approach is to switch them off when their activity levels are low, such as during periods of low load or minimal traffic requirements. This approach is referred to as strategic sleeping, and it can be characterized by a function F: [0, 1] → [0, 1]. Specifically, when the coverage area of the base station in the active state is denoted as 'x', the probability of operation is represented by F(x). The probability of entering sleep mode is determined by the product of the likelihood of sleep, denoted as l. F(x), as depicted in Fig. 3. This sleep mode method follows a load-aware policy that can encompass multiple traffic profiles within the optimization problem [32].

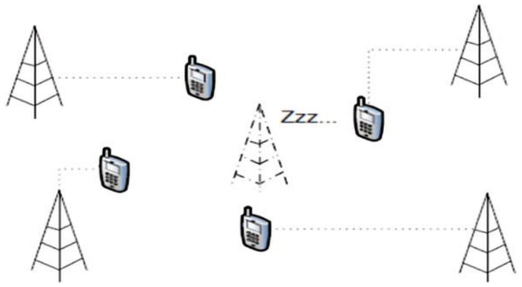


Fig. 2. Working of random sleeping [12].

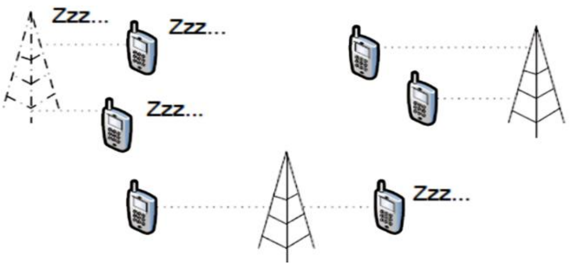


Fig. 3. Process of dynamic sleep strategy [12].

B. Particle Swarm Optimization

The optimization problem is addressed through PSO, which involves iterative processes with a global best solution. PSO is a computer-based method that aims to improve the solution of a specific quality measure. It utilizes a simple mathematical procedure based on the position and velocity of particles to generate a population of potential solutions. The best-known positions in the search space and the local best-known positions of each particle, which are updated as other particles find better spots, both have an impact on how each particle moves. This mechanism helps direct the swarm's attention toward the most favorable choices. The process flow of PSO is shown in Fig. 4.

The equation utilized to calculate the position of swarms and the velocity at which the swarm, moves are given below. In general, two swarms are considered are performing the optimization position. In this work, three swarm technique is considered to further enhance the level of optimization process.

The positions of the selected swarm particles are updated based on swarm technique. The position is calculated using below equations.

$$\mathrm{P_1} = \mathrm{P_Q} - \mathrm{B} \cdot \mathrm{V_Q} \tag{1}$$

$$\mathrm{P_2} = \mathrm{P_R} - \mathrm{B} \cdot \mathrm{V_R} \tag{2}$$

$$\mathrm{P_3} = \mathrm{P_S} - \mathrm{B} \cdot \mathrm{V_S} \tag{3}$$

P_1, P_2 and P_3 are the position of swarms (features) which are updated w.r.t P_Q , $P_R and$ P_S. Here P_Q , P_R and P_S are the initial position of the swarms (features). Where V_Q, V_R and V_S are the velocity calculated using below equation

$$\mathrm{V_Q} = |\mathrm{C} \cdot \mathrm{P_Q}(\mathrm{t}) - \mathrm{P}| \tag{4}$$

$$\mathrm{V_R} = |\mathrm{C} \cdot \mathrm{P_R}(\mathrm{t}) - \mathrm{P}| \tag{5}$$

$$\mathrm{V_S} = |\mathrm{C} \cdot \mathrm{P_S}(\mathrm{t}) - \mathrm{P}| \tag{6}$$

where B and C are the vector coefficients which are calculated as,

$$\mathrm{B} = 2\mathrm{b} \cdot \mathrm{r_1} - \mathrm{b} \tag{7}$$

$$\mathrm{C} = 2 \cdot \mathrm{r_2} \tag{8}$$

b is linearly decreased from 2 to 0 over the course of iterations and r_1, r_2 are random vectors. To generate a better position, the information of best position P is used in PSO. In this the best position is considered as best features.

$$\mathrm{P} = \frac{\mathrm{P_1}+\mathrm{P_2}+\mathrm{P_3}}{3} \tag{9}$$

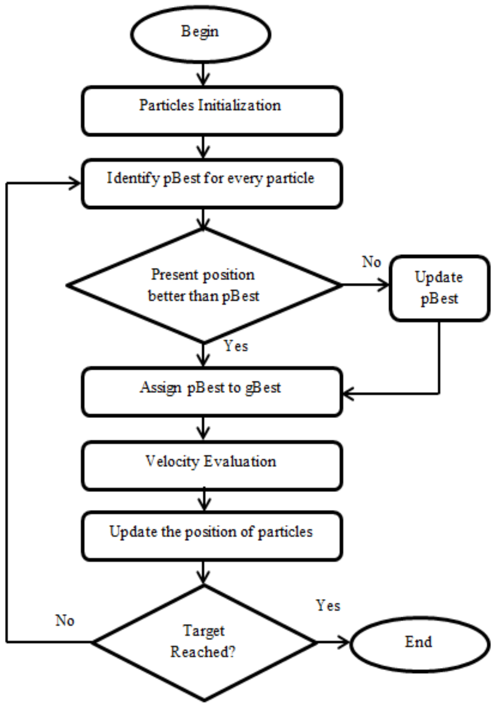


Fig. 4. Basic flowchart of PSO.

C. System Model

Widespread coverage is required for the deployment of cellular networks in 5G. User interference gets more complicated as each small cell supports more users. In a 5G network, this study focuses on a two-tier network structure with a central mega cell and "n" tiny cells. A single Macro Base Station (MBS) and "n" Small cell Base Stations (SBSs) are taken into account by the implemented approach. While each SBS provides for a number of Small-cell User Equipment's (SUEs), the MBS serves several Macro-cell User Equipment's (MUEs) [33]. While the SBSs are dispersed at random around the area, the MBS is carefully positioned in the middle of its service area. Each tiny User Equipment (UE) is also inside the SBS's respective coverage region. The energy saving operation near base stations is represented in Fig. 5.

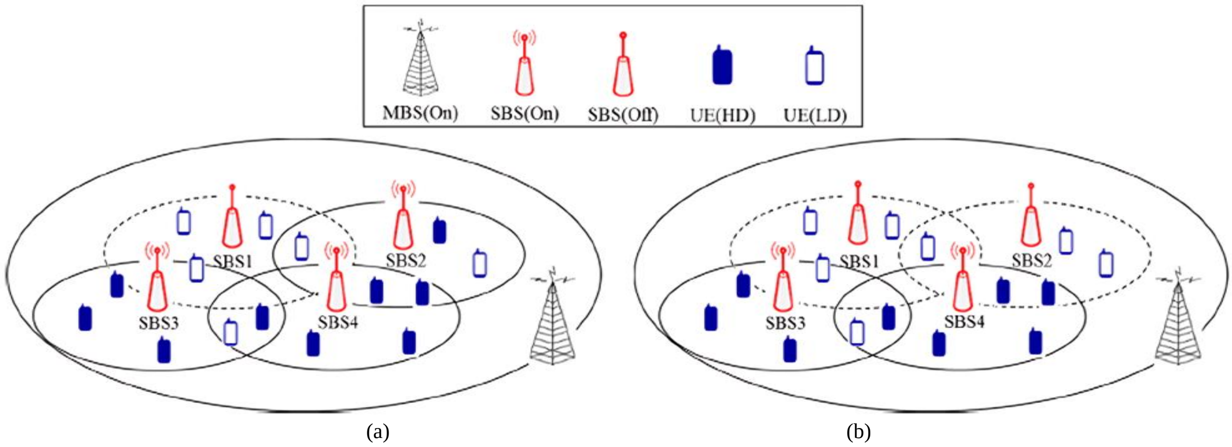


Fig. 5. Energy saving operation process near BS (a) before saving the energy (b) after saving the energy.

The uplink scenario is considered, and the Additive White Gaussian Noise (AWGN) variance is N_0. Here BS_0 and BS_i represent MBS and i^{th} SBS. The received signal-to-interference noise ratio (SINR) γ_{ij} of user pair (i, j) at BS_i is calculated from [17]:

$$\gamma_{(i,j)} = \frac{p_{(i,j)} g_{(i,j)}}{\sum_{(m,n)\neq(i,j)} g^{i}_{(m,n)} p_{(m,n)} + N_0} \tag{10}$$

Here (i, j) is termed as j^{th} small user in i^{th} small base station. The same way (m, n) is n^{th} small user in the m^{th} small base station. $p_{(i,j)}$ is the power near SU and SBS. $g_{(i,j)}$ is the gain function.

1) Network design with sleep strategy

In this section, the cellular sleep method is introduced to address the issue of overlapping cellphone coverage in the dense cellular deployment of the 5G two-tier network architecture. Deploying dense cells in the 5G network offers advantages such as increased communication capacity and reduced dead zones. However, it also presents challenges, with overlapping cellphone coverage being a prominent issue. This overlap brings various drawbacks to the communication system, including increased energy consumption, resource wastage, and higher spectrum occupancy. The sleep method proposed in this paper aims to tackle these issues. By modifying the sleep strategy, redundant workstations are deactivated and transitioned into a sleep state mode. This sleep method and network architecture combination further enhances energy efficiency. The study begins by developing a sleep strategy to optimize power utilization and maximize revenues based on the new architecture.

Fig. 6 illustrates an example of the sleep approach. Initially, three SBSs are shown, and users within the coverage areas of SBS1 and SBS3 can access communication services provided by SBS2. Consequently, SBS2 can be put to sleep mode to conserve energy in the system. The sleep technique reduces power consumption in the 5G communication network. Thus, our sleep technique aligns with the motivation to improve energy efficiency within the network.

In the integrated process, two primary factors that require consideration are the transmission rate of users and the cost function. A communication pair's rate of transmission is described as follows:

$$R_{(i,j)} = W\, log_2\left(1 + \frac{p_{(i,j)} g_{(i,j)}}{\sum_{(m,n)\neq(i,j)} g^{i}_{(m,n)} p_{(m,n)} + N_0}\right) \tag{11}$$

The utility function of cellular i is given as,

$$U_i = R_i - c\sum_{j=1}^{n} p^{*}_{i,j} \tag{12}$$

where W stands for bandwidth, n for the number of mobile users, R_i for their combined transmission rate, and c for their earning potential. The utility function U_i is optimized to produce the ideal power and $p^{*}_{i,j}$ is the optimal power.

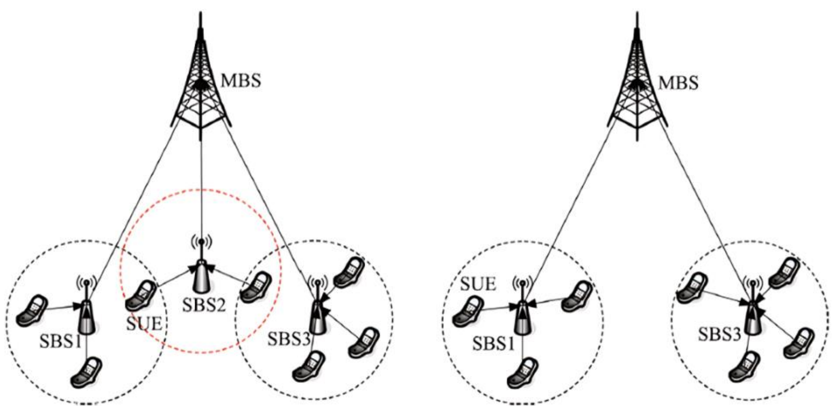


Fig. 6. Sleep state topology- before sleep (left) and after sleep (right) [34].

2) Design of sleep strategy conditions

The implemented assessment utility combines power allocation and sleep approach to optimize overall Small Cell User Equipment (SUE) profits. The following conditions are detailed for the sleep approach of the Small Base Stations (SBSs):

C1: When a SBS's user is within the coverage area of two or more SBSs, that particular SBS is considered as a candidate for entering sleep mode.

C2: If two or more SBSs provide coverage to all SUEs in the cellular network over a given timeframe, the SBS with the highest match is selected as the candidate for entering sleep mode. However, if any combination of SBSs does not cover all SUEs, the SBSs will continue to operate.

C3: Suppose the earnings of the cellular network fall below an acceptable threshold, denoted as ξ, and satisfy the condition Ui ≤ ξ (where Ui represents the earnings of the SBS). In that case, the SBS is considered to be in a sleep state.

If an SBS fulfills all three conditions, it will be chosen to maximize total revenues.

3) Objective function

To utilize the optimization technique, an objective function needs to be defined to obtain the optimal power allocation and optimal sleep state. The main objective function considered in this work for optimizing the power allocation near the Base Station (BS) is derived from [17]. The objective function can be expressed as follows:

$$p_{i,j}^{*}=\frac{\frac{\alpha}{\ln 2}}{c+\sum_{m,n}\left(\frac{\alpha\, g_{i,j}}{\ln 2\, p_{m,n}g_{m,n}}SIR(\tilde{p}_{i,j})\right)+\lambda_k\bar{g}_{i,j}\ln(1-\varepsilon_{i,j})+\sum_{k\neq i,j}\lambda_k g_{i,j}\left(2^{\frac{R_0}{W}}-1\right)} \quad (13)$$

where α is the variable used for regulating after using sleep strategy, λ stands for the Lagrangian function and is given by the follow equation.

$$\lambda_k=\bar{g}_{i,j}p_{i,j}\ln\left(1-\varepsilon_{i,j}\right)+\left(2^{\frac{R_0}{W}}-1\right)\left(I_{i,j}+N_0\right) \quad (14)$$

Here the function $I_{i,j}$ is the total value of interference. During the application of optimization procedures, the value should be continuously updated until the optimal power allocation is achieved. In this study, both iterative and PSO techniques were employed to maximize the power. Eqs. (15) and (16) are utilized to derive the primary objective function.

The updated power and Lagrangian function can be represented by the following equations:

$$\lambda_k(t+1)=\lambda_k(t)+\mu_0 S_{\lambda_k} \quad (15)$$

Here S_{λ_k} is said to be the sub-gradient of λ_k.

$$p_{i,j}(t+1)=p_{i,j}(t)+\lambda_k\frac{\frac{\alpha}{\ln 2}}{c+\sum_{m,n}\left(\frac{\alpha\, g_{i,j}}{\ln 2\, p_{m,n}g_{m,n}}SIR(\tilde{p}_{i,j})\right)+\lambda_k\bar{g}_{i,j}\ln(1-\varepsilon_{i,j})+\sum_{k\neq i,j}\lambda_k g_{i,j}\left(2^{\frac{R_0}{W}}-1\right)} \quad (16)$$

4) Implemented optimization process

The power and optimal state, obtained through MPSO, are evaluated. MPSO is an emerging technique widely employed in various applications to obtain the global best solutions. This project's evaluation focuses on power optimization in conjunction with sleep strategies. The operational procedure of MPSO, as described in Section III, and the algorithm employed for evaluating minimal power are discussed in detail. The working of optimization technique locally and globally is shown in Fig. 7.

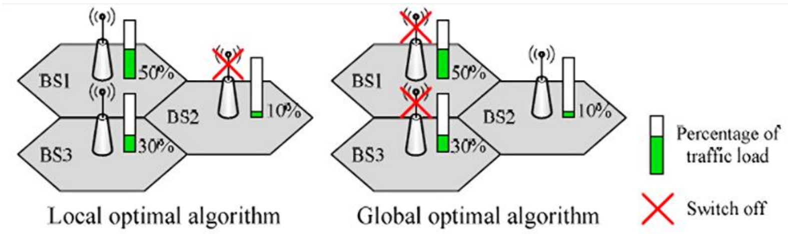


Fig. 7. Local optimization vs Global optimization (PSO).

D. Experimental Environment

The entire setup of work performed using a matlab software tool version 2021a. The requirement of system is windows 7 OS, 8 GB RAM, 512 GB hard disk. The process flow of paper is designed to obtain the good working results in saving of power near the base-stations. The network is designed by randomly assigning number of users, radius of macro cells, radius of femto cells. The results obtained using the proposed model helps in transferring of more data among the users by utilizing less power.

Algorithm 1. PSO based Sleep Strategy
Step 1: Initialize each particle at random, assign power to p_0, and set $t = 0$ for iterations.
Step 2: Set the value of threshold ε_{ij}
Step 3: Repeat
Step 4: Update the power value based on the sleep strategy of MBS.
Step 5: Identify new topology
Step 6: Update the λ, that is the Lagrangian multiplier
Step 7: Obtain the pbest solution
Step 8: Update the power value compared to pbest as $p_{i,}j(t+1)$.
Step 9: Update the λ value as $\lambda_k(t+1)$.
Step 10: Find the global best solution $p^*_{i,j}$.
Step 11: End if max iterations reached or end if optimal power and optimal sleep state reached.
Step 12: Else go to step 4.

IV. Results and Discussion

The proposed power control and sleep strategy scheduling in a two-tier network are evaluated using numerical findings in this section. Table II displays some system parameters. For the simulation, the number of total SBSs and SUEs used within the coverage zone are 9 SBSs and 18 SUES. The allocation of users was performed randomly during the implementation. It is important to note that the specific values of ε_{ij} for MUEs and SUEs were identical. Whenever a parameter was modified, the corresponding plot was updated accordingly.

TABLE II. System Parameters for Evaluation [34]

Parameter	Value
Users (n)	18
Radius of Macro cells (R)	250 m
Radius of Femto cells (r)	30 m
Max value of transmission power (ρmax)	1 W
Frequency of carrier (f)	2000 MHz
Bandwidth of system (w)	$10^{0.5}$
Variance factor of AWGN (N_0)	10^{-6}
Threshold of outage probability (ε_{ij})	0.1
Price factor of the objective function (c)	0.1
The threshold of earning (ξ)	0.2
Mean of gain ($\overline{g}_{ij}$)	$10^{-2.5}$
Rate of threshold (R_0)	0.25
Length of iterative step (μ_0)	0.01

Fig. 8 illustrates the power values at 50 iterations. Without the sleep approach, the power contrast is 0.7 W. After implementing the sleep approach with the IOA, the power value decreases to 0.5 W; with the PSO it decreases to 0.4 W. Before applying the sleep strategy, the users experience higher power levels, indicating more interference in the system. However, after implementing the recommended sleep algorithm, the users encounter reduced interference, leading to lower power levels. This power reduction signifies a decrease in interference. Fig. 8 also demonstrates the convergence of the contrast rate and power. The red, blue, and yellow lines represent different methods used to compare the results. The blue line corresponds to the power values before implementing the sleep strategy, the red line corresponds to the power values after using the sleep strategy with IOA, and the yellow line corresponds to the power values after using the PSO.

When considering the rate at 50 iterations, the contrast rate before the sleep strategy is 1.2 B. After applying the sleep strategy with IOA, the contrast rate increases to 1.4 B; PSO further increases to 1.5 B. In terms of usage rate, interference, and noise are crucial factors.

The interference decreases proportionally as the power is reduced. Consequently, the rate is higher than before implementing the sleep strategy, indicating improved performance.

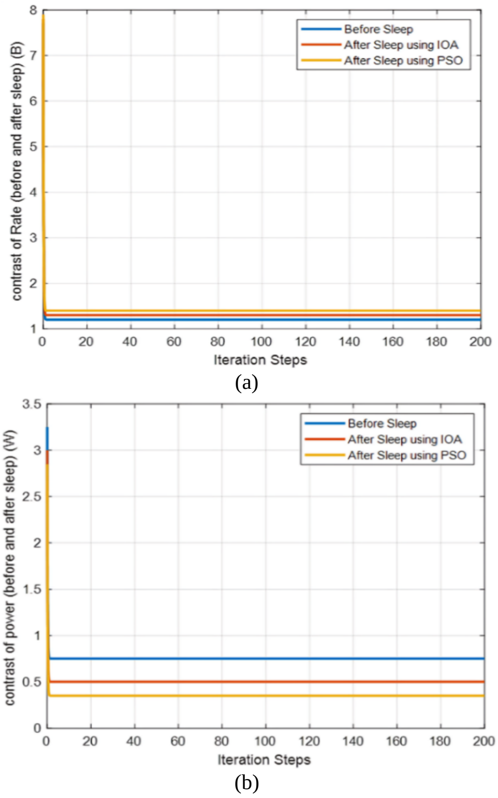


Fig. 8. (a) Contrast of Rate (b) Contrast of power, with respect to number of iterations.

In this paper, the term “earning” is used to evaluate the system’s overall performance from an economic perspective. The earning is directly related to power consumption, meaning that as power consumption decreases, the earnings increase. The curve on the graph represents the total profits of the system. Fig. 9 illustrates the earnings before and after implementing the sleep approach. Evidently, the earnings before applying the sleep approach are lower than the earnings after implementing the sleep method. Specifically, the earning before the sleep strategy is 1.2, while after applying the sleep strategy with IOA it increases to 1.5, and with PSO it further increases to 1.8. These results indicate that the sleep method significantly enhances the performance of the cellular system. This improvement can be attributed to the fact that when the SBSs enter sleep mode, the rate of the system increases while the power consumption decreases.

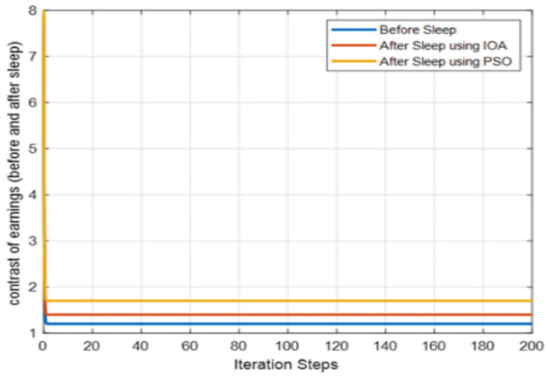


Fig. 9. Convergence of users' total earnings.

Despite the reduction in the number of active SBSs, the earnings rise. Therefore, the sleep method effectively conserves base station resources and reduces power consumption wastage.

Fig. 10 depicts the energy efficiency achieved using different techniques. The system's energy efficiency is influenced by parameters such as "R" and "p". Before implementing the sleep approach, the energy efficiency is lower than the post-sleep strategy scenario. At iteration 50, the energy efficiency value before the sleep strategy is approximately 2.7. However, after employing the sleep strategy with IOA, the energy efficiency increases to 4.1, and with PSO, it further rises to 6.1. This improvement is attributed to the fact that when the SBSs enter the sleep stage, the system's rate increases while the power decreases, resulting in improved energy efficiency compared to the pre-sleep condition. Fig. 10 also reveals that increasing the number of iterations leads to an improvement in energy efficiency. The values of energy efficiency at various iterations are presented in Table III. It can be observed that after a certain point of iteration, the energy efficiency becomes stable, indicating that the maximum power optimization has been achieved.

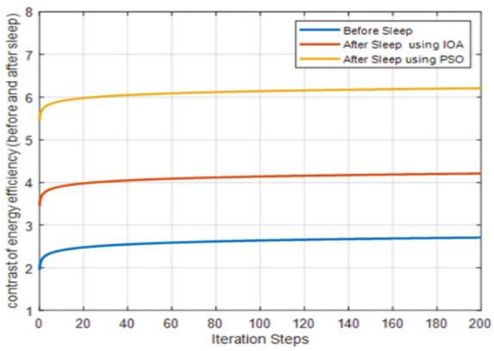


Fig. 10. Convergence of user total energy efficiency.

TABLE III. COMPARISON OF ENERGY EFFICIENCY

Number of Iterations	Before Sleep Strategy	After sleep strategy using IOA [34]	Sleep Strategy using PSO
10	2.2%	3.8%	5.8%
20	2.3%	3.85%	5.9%
30	2.4%	3.9%	5.95%
40	2.5%	3.95%	6%
50	2.6%	4%	6.05%

Fig. 11 illustrates the power consumption by users under various base stations. In this process, one user is randomly selected from each cellphone. Initially, there were nine operational base stations before implementing the sleep strategy. However, only six base stations remain active after applying the sleep technique. Specifically, base stations 2, 5, and 8 enter sleep mode, resulting in zero power consumption for those base stations. It is evident from Fig. 11 that the power depletion at different BSs before implementing the sleep strategy is higher compared to the power consumption after applying the sleep strategy. This reduction in power consumption is due to lower interference experienced by the users from other users. Fig. 11 further highlights the feasibility and effectiveness of the sleep technique. For example, considering base station 4, the power users consume before implementing the sleep strategy is 0.035 W. However, after employing the sleep strategy with IOA, the power consumption decreases to 0.015 W; with PSO, it further decreases to 0.009 W. This reduction in power consumption is attributed to the reduced interference experienced by the users from other users in the system.

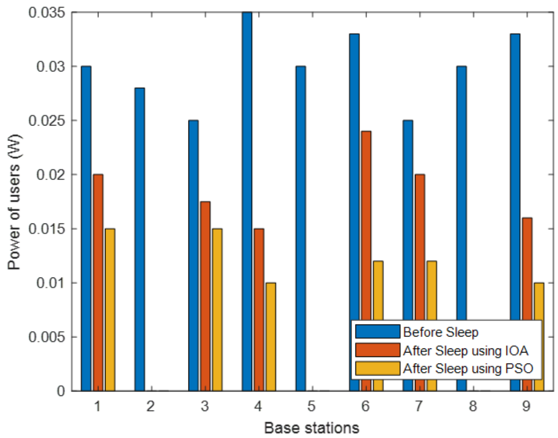


Fig. 11. Power results before and after sleep.

Table IV presents the power usage of different users associated with their assigned base stations using the implemented methodology. The power results are evaluated considering a maximum power limit of 1 W. It is evident that, through the optimization technique, the power consumption has been significantly reduced, even reaching zero for certain base stations.

TABLE IV. COMPARISON OF CONSUMPTION OF POWER

BS/Method	Before Sleep Strategy	Sleep Strategy with IOA [34]	Implemented sleep Strategy with PSO
1	0.03 W	0.020 W	0.014 W
2	0.0258 W	0 W	0 W
3	0.025 W	0.018 W	0.015 W
4	0.035 W	0.015 W	0.011 W
5	0.032 W	0 W	0 W
6	0.034 W	0.024 W	0.013 W
7	0.024 W	0.022 W	0.013 W
8	0.031 W	0 W	0 W
9	0.0032 W	0.0156 W	0.01 W

V. Conclusion

The increasing energy consumption poses significant challenges related to global warming. Mobile communication networks have garnered significant attention due to their substantial contribution to overall energy consumption in the field of ICT. A technique for controlling power and implementing a sleep approach in a 5G two-tier network system has been developed to address these challenges. The proposed methodology aims to improve the system's performance. Optimization solutions are obtained using a particle swarm optimization approach, which is then compared with an iterative optimization approach. Additionally, the sleep approach is employed to enhance the system's revenues. By combining the sleep strategy with power control, the system achieves higher profits and improved energy efficiency with reduced energy usage. The sleep technique effectively conserves base station resources, reduces spectrum wastage, and minimizes energy waste.

In the future, it is important to consider the energy usage of user equipment in a multi-macro cell environment, as there is significant energy waste in such scenarios. Furthermore, as user equipment communicates with both MBSs and nearby SBSs, the distance between the user equipment and the MBS becomes crucial. Similar sleep approaches can also be applied to the MBSs, and implementing cutoff restrictions for the MBS can help reduce the distance between the MBS and the UE. This approach would contribute to further energy savings and optimization in the network.

Conflict of Interest

Authors declare that there is no conflict of interest. Manuscript and provided critical feedback. All authors had approved the final version.

Author Contributions

Conceptualization: N.R.Y., P.Y., P.S.K.., and S.M.; Methodology: V.A.K., L.N.J.G., O.P.S., and N.R.K.V.; Data Collection: L.T.R.., K.S.B.., and L.K.P.; Data Analysis: N.R.Y. and B.B.D., and S.M; Data Interpretations: N.R.Y., V.A.K., and B.B.D.; Writing-Original draft preparation: N.R.Y. and S.M.; Writing-review and editing: N.R.Y. and V.A.K.; Supervision: N.R.Y.; All the authors have read and agreed to the published version of the Manuscript.

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