Journal of Theoretical and Applied Information Technology
31st July 2025. Vol.103. No.14

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

HYBRID OPTIMIZATION TECHNIQUES FOR MOBILITY-AWARE, ENERGY-EFFICIENT SMALL CELL DEPLOYMENT IN 5G NETWORKS

S. VINODH KUMAR[1*], A. VIJAYALAKSHMI[2], A. PACKIALATHA[3], B. EBENEZER ABISHEK[4]

[1*]Research Scholar, Department of Electronics and Communication Engineering, VELS Institute of Science, Technology and Advanced Studies (VISTAS), Chennai, India.

[2]Professor and Research Supervisor, Department of Electronics and Communication Engineering, VELS Institute of Science, Technology and Advanced Studies (VISTAS), Chennai, India.

[3]Associate Professor and Co-Supervisor, Department of Computer Science and Engineering, VELS Institute of Science, Technology and Advanced Studies (VISTAS), Chennai, India.

[4]Associate Professor, Department of Electronics and Communication Engineering, KCG College of Technology, Chennai, India.

E-mail: [1*]vinosai@gmail.com, [2]vijayalakshmi.se@vistas.ac.in, [3]packialatha.se@vistas.ac.in, [4]ebenezer.ece@kcgcollege.com

ABSTRACT

Expanding wireless communication networks is necessary to meet the growing number of mobile devices and the demand for faster internet. One practical way to increase network capacity and coverage in heavily populated regions is to deploy tiny cells. Smaller cells require more energy, increasing operating costs and negatively affecting the environment. Traditional deployment approaches ignore user mobility, despite its substantial impact on network performance. We present a strategy for microcell deployment in 5G networks, utilizing hybrid optimization techniques to address issues related to mobility awareness and energy efficiency. The planned teenTo improve data transfer capacity and increase user density in tiny cells, the suggested strategy clusters users using a Modified Smell-Bees Optimization (MSBO) algorithm. This research introduces a Gannet Optimal Induced Cuckoo Search (GOCS) approach to grouping microcells into optimal locations while accounting for various design limitations. This book lays out an Improved Coral Reef Optimization (ICRO) approach that takes reliability criteria into account for better coral reef optimization. Measures such as connection quality, user mobility, congestion rate, and mean time to failure are part of these criteria. Assisting in the setup of compact base stations is the goal of this plan. Simulations conducted in the Google Colab environment greatly enhance important Quality of Service (QoS) measures. The MSBO-GOCS-ICRO model is better than the well-known GSCP, TIPA, and ECM-BPSD models in many ways. For example, it cuts convergence time by 49%, increases the number of small base stations in use by 64%, and makes the network 154% more energy efficient. These findings indicate that the suggested approach is the optimal choice for the deployment of tiny cells in 5G networks.

Keywords: *5G networks, Small cell deployment, Hybrid optimization, Energy efficiency, Mobility management, Quality of Service.*

1. INTRODUCTION

Massive upgrades to mobile communication technology are required to meet the ever-increasing demands of 5G networks, which include more complex multi-carrier spectrum utilization, denser base stations, and greater bandwidth. Picocells, microcells, femtocells, and micro base stations are crucial to this advancement because they provide more targeted coverage with lower transmission power consumption than traditional macro cell stations (MBS) [1-2]. Building small cell base stations (SCBS) improves network performance and user experience while reducing energy consumption and coverage expenditures. Deploying 5G networks is hampered by greater capital expenditures, charges associated with spectrum acquisition, and site procurement expenditures that exceed those of 4G networks. These issues arise due to the complexity of the infrastructure and the increasing demand for capacity. 5G devices are more expensive since they include radio frequency (RF) components and have better capability [3-4]. We need to create new technologies to monitor energy use and process complexity, with the dual goals of increasing efficiency and decreasing expenditures. I have read [5-6] to the best of my knowledge. Femtocellular networks need stringent security protocols to protect user data because of their more adaptable design compared to traditional cellular systems [7]. The unique requirements of the sent data and the various communication levels should be considered when developing security protocols [8]. It is far more difficult to optimize the sites of small cells when dealing with changes in mobile user pathways and traffic demands. This is particularly true in situations where there is a lack of detailed data on energy storage and transportation patterns [9-10]. Recent research has focused on several issues related to small-cell deployment in 5G networks. Researchers have investigated power adaptability and self-adjusting bandwidth as potential ways to improve efficiency and coverage. [11]. Ideas for adaptive cooperative communication systems employ optimum communication ways to optimize network benefits. [12-13]. To improve the energy economy and optimize network performance, researchers have examined user-focused communication approaches and adaptive small-cell deployment frameworks [14-17]. Ascending from lowest to highest. Additional research has focused on ways to efficiently allocate small cells in hyper-dense distributions and develop energy-efficient solutions for small cell networks operating in very dense environments [18]. These sources include: [19-20]. Finding a satisfactory medium between energy usage and network performance, as well as addressing practical deployment challenges, are at the heart of these investigations. It is necessary to use fault-tolerant solutions that use evolutionary approaches in signal processing on FPGA systems [21] for highly populated 5G small cell implementations to be more reliable and use less energy. Energy efficiency and mobility control take center stage in small cell networks. Using cross-layered reconfigurable hierarchical protocols to enhance routing algorithms might solve both of these problems [22]. Additionally, we develop strategies for resource allocation in network slicing using Gaussian Naive Bayes approaches, which are based on bagging. These strategies are crucial for the dynamic optimization of small-cell installations [23]. Scheduling methods with multiple clusters and channels are useful for managing traffic efficiently in dense 5G environments with small cells so that data collection is faster and delays are lessened [24]. In addition, software-defined networking (SDN) and edge computing scheduling approaches provide excellent foundations for improving the performance of small-cell deployments. This allows for improved data transfer and computation offloading in 5G networks [25]. The study's results shed light on how to improve mobility management and decrease energy consumption via hybrid optimization to overcome challenges to the deployment of tiny cells in 5G that are energy efficient. In this study, we use a combined optimization strategy to enhance the energy efficiency and movement awareness of small cell deployment. An enhanced Coral Reef Optimization algorithm that gives priority to small base station deployment based on reliability metrics is one of the notable advancements in this work. Another is an improved user clustering algorithm that uses a modified Smell-Bees Optimization algorithm. The third advancement is an optimized placement of small cells using a Gannet Optimal-induced Cuckoo Search algorithm. Simulations on Google Colab demonstrate an improvement in overall network performance and quality of service measures, allowing for an evaluation of the proposed strategy.

1.1. Contribution

- This study introduces a novel mobility-aware small cell deployment strategy in 5G networks by integrating three hybrid optimization techniques: Modified Smell-Bees Optimization (MSBO) for user clustering, Gannet Optimal Induced Cuckoo Search (GOCS) for optimal microcell placement, and Improved Coral Reef Optimization (ICRO) for enhancing network reliability.
- The proposed MSBO-GOCS-ICRO model significantly outperforms existing methodologies (GSCP, TIPA, ECM-BPSD), achieving a 49% reduction in convergence time, a 64% increase in the number of active small base stations, and a remarkable 154% improvement in network energy efficiency.
- Simulations conducted in the Google Colab environment demonstrate substantial enhancements in key Quality of Service (QoS) metrics, including connection quality, congestion rate, and mean time to failure. This validates the model's practical feasibility for real-world 5G deployments.

1.2. Problem Statements

- Traditional small cell deployment strategies in 5G networks fail to account for user mobility, leading to inefficient resource allocation, increased energy consumption, and higher operational costs. Existing approaches struggle to balance network performance and sustainability while addressing real-time mobility dynamics.
- Current deployment models lack effective optimization techniques for determining optimal microcell locations, resulting in poor network coverage, congestion, and reduced Quality of Service (QoS). The absence of a comprehensive hybrid optimization approach limits the ability to enhance network reliability, data transfer capacity, and overall efficiency.

2. RELATED WORKS

This section presents the research problem, enumerates pertinent literature, and provides a thorough review of prior studies on small cell implementation in 5G networks. This article addresses major topics like dependability metrics, optimization approaches, and clustering algorithms. Table 1 enumerates the deficiencies in the existing corpus of research and illustrates how the proposed model addresses them.

2.1 Clustering Algorithms

Bashir et al. introduced a technique for precise phase monitoring of a Digitally Controlled Oscillator (DCO) using an LC tank [26]. DesignWe recommend putting the system in wideband mode when designing future wideband digital polar transmitters. ke degradation owing to spectrum limitations and a very complicated network design restricts this method, despite its benefits.

To determine small cell deployment and uplink resource allocation influenced by user input, Gao et al. [27] presented a hybrid multi-agent strategy that enables a macrocell Base Station (MBS) and several Small Base Stations (SBS) to collaboratively work together. A distributed SBS system uses a stochastic game model to cooperatively administrate the allocation of uplink resources, while the central MBS system uses an anti-corruption method. Covering broad outdoor spaces with little cells is a challenge with this method.

Mugume et al. [28] created an integrated network multi-user connection model based on Poisson's Point Process (PPP). Under different constraints, this model permits exact assessments of energy efficiency. Although it enhances the small-cell density distribution framework, sharing spectrum across cells is still complicated.

2.2 Optimization Techniques

In a study by Xiao et al. [29], they suggested using reinforcement learning to manage power in dense small-cell environments so that downlink inter-cell interference is reduced and energy efficiency is raised. The technology employs a deep reinforcement learning technique to enhance network performance while lowering power consumption. This approach fails when simultaneously optimizing for energy and throughput. For millimeter wave downlink, Wang et al. [30] proposed a K-layer heterogeneous cellular network with user-driven small cell deployment. Using Thomas Cluster processes, the model analyzes user activity and the probability of cells merging close to small cell base stations. Despite improving the Signal-to-Interference-and-Noise Ratio (SINR), this method's assumption of complete coverage makes it impractical in densely populated metropolitan areas. Rezaabad et al. [31] introduced the NSGA-II approach to find the lowest number of W-BSs and U-BSs required to satisfy certain coverage and throughput requirements. The method lowers deployment costs and improves cell scheduling, but it comes with a significant rise in processing overhead.

2.3 Reliability Metrics

Ghatak et al. [32] used Poisson Line Processing (PLP) to predict urban visual paths for several SBSs operating in the sub-6 GHz and millimeter-wave bands. The millimeter wave interference pattern disperses tiny particles over pedestrian walkways. Although this technique enhances the downlink data flow, its primary drawback lies in its susceptibility to interruption. Lahad et al. [33] presented a Time Division Duplex (TDD) model that modifies the distribution of resources between the uplink and downlink. The concept combines a vast network of macrocells and tiny cells to increase spectral efficiency. The method uses capacity expressions as a gauge of decoupling gain while ignoring the complexities of backhauling and network scalability. Li et al. [34] developed an edge server deployment method to optimize the number and placement of servers in ultra-dense networks (UDNs). Although it reduces response time and spreads the load across edge servers, backhauling issues ultimately restrict the system's performance.

Venkateswara Rao et al. [35] showed new affinity spread grouping and load-adjusted route selection algorithms for the dynamic 5G virtual microcell and backhaul architecture. By coordinating with UE-VBS, which has VRNs and VSCs at specific locations, the system provides a real-time mobile infrastructure that enhances data rate and throughput by adapting to RAN demand. Table 1 lists the primary research gaps in the body of literature and explains how the proposed model in this study fills them.

We properly classify malware using CNN. We clean and enhance the dataset to make the model adaptable. Thorough testing and optimization provide 98.47% Trojan horse detection. Malware detection is accurate using deep learning. CNN model characteristics show Trojan horse attacks. It offers complete cyber security and raises awareness of viruses. Deep learning may enhance Trojan horse cybersecurity, according to our research [36].

Blockchain streamlines processes, saves costs, enhances security, and boosts transparency, according to this research. Edge AI vehicle detection, counting, and recognition algorithms in smart transportation are being studied. Blockchain's promise in smart energy trading, automobile transfer, and encrypted communication is also noted. This research reveals new blockchain and edge AI smart city applications to academics [37-38].

Table 1: Summary of Research Gaps.

Ref.	Methodology	Technique Used	Findings	Research Gaps
[26]	Small cell deployment model	SVM, LSTM based controllers	Delivery ratio, energy consumption	Spectrum shortage, complex network infrastructure
[27]	Interference control for ultra-dense SCs	CNN (RL-based algorithm)	Energy consumption, throughput	No joint optimization of energy and throughput
[28]	Spectrum sharing and SC deployment	Hybrid multi-agent approach	Energy consumption, spectral efficiency	Difficult to cover large outdoor areas with small cells
[29]	Small cell deployment model for 5G	Poisson Point Process (PPP)	Energy consumption	Complexity due to inter-cell spectrum sharing
[30]	SC deployment model for urban areas	Poisson Line Cox Process (PLCP)	SINR	High sensitivity to blockages
[31]	User-centric small cell deployment	Conditional neural network	SINR	Unrealistic assumptions of ubiquitous coverage
[32]	5G SC deployment	NSGA-II	SINR, coverage rate	High computational overhead
[33]	Virtual small-cell deployment	MAPC and MLGP algorithm	Throughput, delay, jitter	Unsuitable for dense networks due to backhaul limitations
[34]	Uplink/downlink access control in 5G	TDD and DUDA statistical model	Spectral efficiency, energy consumption	Does not address cell planning and energy optimization
[35]	Edge server deployment in 5G small cell	Vector Quantization (VQ)	Communication time, queue time	Backhauling not addressed, limiting overall system performance

3. SYSTEM MODEL AND PROBLEM DEFINITION

3.1. Problem Definition

There are new issues with energy efficiency and network performance that arise from deploying small cells in 5G Ultra-Dense Tiny Cell Networks (UDSCN). Venkateswara Rao et al. [36] suggested a microscopic cell sorting technique based on particle swarm optimization (PSO) and efficient cell modeling (ECM) to address these issues. The BPSD algorithm maximizes the distribution of small base stations (s-BS) to enhance network performance, spectrum efficiency, and energy usage. The ECM algorithm, on the other hand, gives s-BS and User Equipment (UE) more priority. Despite these improvements, traditional 5G network designs often disregard the major energy efficiency issues caused by the proliferation of tiny cells.

Small cells, such as femtocells, picocells, and microcells, present considerable potential for enhancing connectivity and data transfer rates. Nonetheless, the implementation of dense small cells poses challenges, especially in regions characterized by fluctuating traffic demands and significant interference. Efficient small cell planning is essential for enhancing network performance and providing adequate coverage in densely populated areas such as shopping centers, gyms, airports, and train stations [26-27]. The static deployment of small cells according to peak traffic demands, common in conventional macro cellular networks, is ineffective for managing mobile traffic fluctuations [31-32]. Numerous studies have insufficiently examined the effects of energy harvesting from various network providers [26-38]. Effective energy harvesting from diverse sources is crucial for enhancing node performance in next-generation technologies.

We propose a hybrid optimization framework that integrates multiple techniques to improve the efficiency of small-cell deployment and mobility management in 5G networks. The research objectives of the proposed model are: firstly, to devise an optimal small cell deployment model that minimizes environmental impact and enhances network efficiency. Secondly, to improve the model for tackling joint optimization issues concerning mobility management and energy consumption. Third, to devise an optimal algorithm for pinpointing the most advantageous locations for small cells, thereby enhancing network performance and Quality of Service (QoS). Ultimately, to validate the proposed deployment model via simulation scenarios to illustrate its efficacy in improving QoS parameters.

3.2. System Model

Figure 1 depicts the system architecture of the proposed model. The model depicts a macro–Base Station(macro-BS) situated at the core of a densely populated 5G network zone, encircled by small Base Stations (mini-BSs) and user devices (users). The network functions with multiple traffic models, such as random, uniform, and pooled traffic patterns.

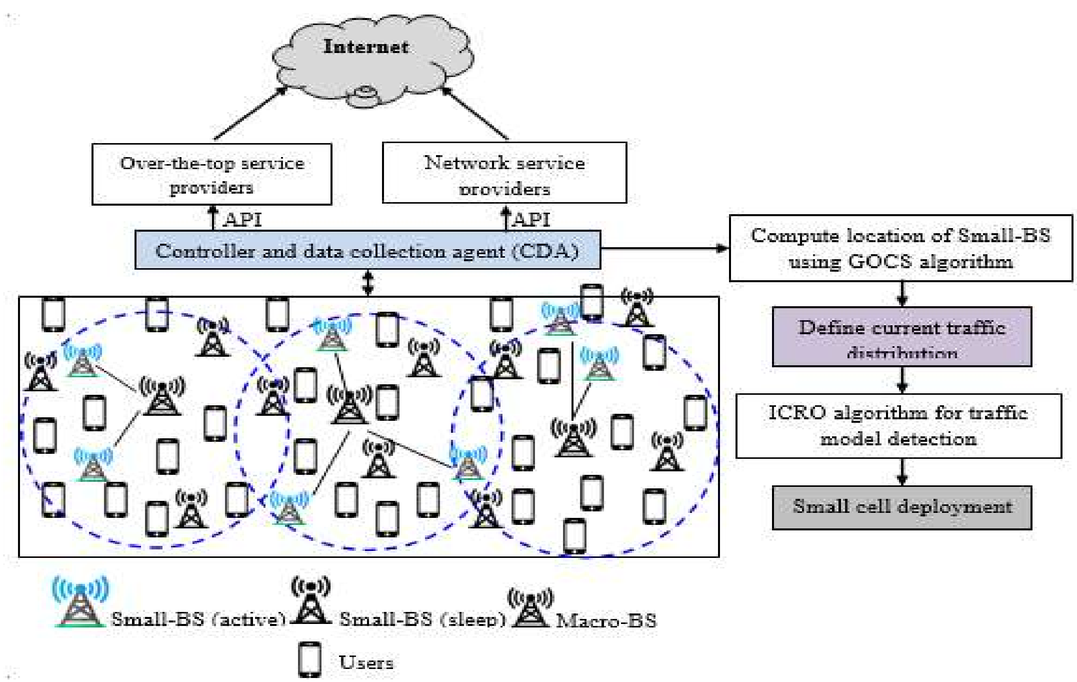


Figure 1: System architecture of the proposed model for small Base Stations (BS) in an ultra-dense area.

The system architecture comprises several essential components. The Controller and Data Collection Agent (DCagent) manages small base stations linked to the macro base station, gathers data, regulates network devices, and interfaces with service providers through APIs. The MSBO Algorithm is employed to create clusters for enhanced user performance, whereas the GOCS Algorithm determines the optimal positioning of small base stations within the network. The ICRO Algorithm predicts traffic patterns and develops a distribution strategy for the deployment of small base stations. The DC agent is essential for making sure that each traffic model has at least one small base station accessible and for positioning them following anticipated traffic patterns.

BS Microswitches can respond to changing traffic needs by dynamically switching between active and sleep modes. The suggested strategy successfully overcomes the fundamental obstacles of integrating tiny base stations into various traffic models, ensuring effective deployment and competent management of changing traffic circumstances.

4. PROPOSED METHODOLOGY

We present a method that uses hybrid optimization approaches to deploy tiny cells in 5G wireless networks that are energy-efficient and responsive to users' mobility needs. The main components of this approach are user clustering, optimization of the placement of tiny base stations (BS), and optimization of deployment based on traffic distribution. They will find a detailed explanation of each stage, along with the mathematical models and methods.

4.1 Clustering

In statistical analysis and machine learning, clustering is a fundamental method for grouping objects into sets that are more similar than others. Our proposed strategy to optimize small-cell deployment involves using clustering to optimally organize network users. We use the Modified Smell-Bees Optimization (MSBO) method to do this. Taking cues from honey bees' foraging habits, MSBO refines the age-old smell-bees optimization technique. The MSBO algorithm improves upon the original technique by adding a more complex pheromone update mechanism and a better way to describe solutions. This allows for better user clustering and faster convergence to an optimum solution. The "Modified Smell-Bees Optimization," or MSBO, algorithm functions as follows:

*Table 2: **Algorithm 1:** Cluster formation using MSBO.*

Input: Quantity $s_{i.1}^{1}$	
Output: Vector $uH_{i.}^{j}$	
1.	Initialize the random population. $$\left[S_1^1, S_2^1 S_3^1, \ldots\ldots S_{qS}^1\right] \quad (1)$$
2.	Define the solution of the primary candidate. $$S_i^1 = [s_{i.1}^1, s_{i.2}^1, \ldots s_{i.nc}^1] \quad (2)$$
3.	Compute the speed of the Bees. $$UH_i^j = \eta_j.S1.\nabla(OG)\middle|s_i^j \quad (3)$$
4.	If j=0 and i=1
5.	Compute speed limit control methodology. $$\left|uH_{i.z}^{j}\right| = Min\left[\left|\eta_j.S1\frac{\partial(OH)}{\partial s_z}\right| r_{i.z}^{j} + \alpha_j.S2.uH_{i.z}^{j-1}\right|, \beta_j.uH_{i.z}^{j-1}\left|\right] \quad (4)$$
6	Conduct a local search at each stage of MSBO. $$P_i^{j+1.n} = q_i^{j+1} + S3.Q_i^{j+1} \quad (5)$$
7.	Update the final best solution.
8.	End

4.2 Computation of Optimal Location of Small-BS

The efficacy of the network depends on determining the best placement for base stations, or small-BSs since it influences coverage, capacity, energy consumption, and interference. We provide the Gannet Optimal Induced Cuckoo Search (GOCS) technique as a solution to this issue. This hybrid optimization technique combines the Cuckoo Search and Gannet algorithms to provide the best results. While a Cuckoo Search algorithm replicates a cuckoo bird's egg-laying maneuver in another bird's nest, a Gannet optimization approach simulates a gannet's diving action. The GOCS algorithm uses these ideas to determine the optimal sites for small base stations while accounting for cost, capacity, coverage, power, interference, and other variables. The following describes how the GOCS algorithm operates:

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

*Table 3: **Algorithm 2:** Compute the optimal location of small-BS using GOCS.*

Input: multiple design constraints of users Output: optimal location of small-BS	
1.	Initialize the random population.
2.	Define Levy's flight condition. $$Y_j^{(s+1)} = Y_j^{(s)} + \alpha \oplus levy(\beta) \quad (6)$$
3.	Define simple rule function. $$t = \alpha_0(Y_i^{(s)} - Y_j^{(s)}) \oplus levy(\beta) \sim \alpha_0 \frac{U}{\lvert V \rvert^{1/\beta}}(Y_i^{(s)} - Y_j^{(s)}) \quad (7)$$
4.	While Do
5.	The dimensions using $U \sim n(0, \sigma_U^2), V \sim n(0, \sigma_V^2)$ $$U \sim n(0, \sigma_U^2), V \sim n(0, \sigma_V^2) \quad (8)$$
6	Pareto optimality is reached when H=1.
7.	Update the final best solution.
8.	End

4.3 Computation of Current Traffic Distribution Model

We suggest modifying the current traffic distribution model using the ICRO technique. This method determines a distribution strategy by analyzing many reliability indicators, including user mobility, connection quality, mean time to failure, and congestion rate. Here's how the ICRO algorithm operates:

*Table 4: **Algorithm 3:** Current traffic distribution model computation using ICRO.*

Input: congestion rate, mean time failure, link quality, user mobility Output: compute traffic model	
1.	Initialize M×N reef size
2.	Create Coral Colony
3.	Evaluate Coral Fitness
4.	Stochastically scatter on the reef with an occupancy rate of r0.
5.	Reiterate
6	Use external broadcast spawning to generate a new population of coral fraction FB.
7.	Employ internal brooding to generate a new population of coral fraction 1-FB.
8.	Assessing the quality of the coral larvae.
9.	Settling of the coral larvae onto the reef substrate.
10.	If ICRO is being executed, implement a 'local search strategy'.
11.	Otherwise, if ICRO is in progress, utilize an 'advanced search strategy'.
12.	end if
13.	Generate new coral populations with the fittest individuals. $$X' = 1 + \frac{\sum_u d_u}{\sum_k l.r_k l} = \frac{x.i}{\sum_{k,} lr_k l} \quad (9)$$
14.	Cull the least fit coral individuals on the reef using Equations. $$g = \frac{1}{x_{max}} \quad (10)$$ $$G_{(u)} = \frac{g_{(u)}}{\sum_1^b g_{(u)}} \quad (11)$$
15.	Continue iterating until the stop condition is met.
16.	Retrieve the most optimal solution.

Journal of Theoretical and Applied Information Technology
31st July 2025. Vol.103. No.14

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

To solve the problems with small-cell distribution in 5G networks, the proposed approach uses sophisticated hybrid optimization methods. The methodology uses three algorithms: the GOCSS algorithm for optimal small cell placement, ICRO for distributing traffic modeling, and MSBO for user clustering, to enhance network performance, efficiency, and energy consumption. Each step focuses on fixing specific issues with small cell distribution to ensure the network meets its coverage, capability, and reliability requirements. These algorithms, when combined, provide the groundwork for improved 5G network architecture, which advances mobile network technology.

5. RESULTS AND DISCUSSION

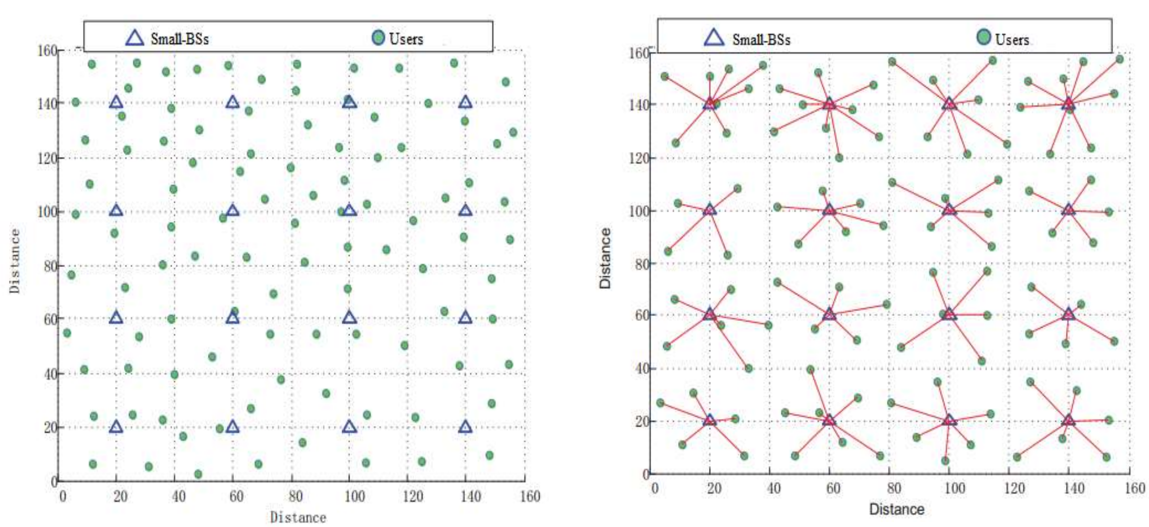
This section compares and contrasts our proposed MSBO-GOCS-ICRO (Multi-Stage Binary Optimisation with GOCS-based Iterative Constrained Relaxation Optimisation) model with previously established models for small cell deployment in 5G networks, before delving into the simulation results. The number of iterations, density of tiny base stations, and density of diverse users are all factors considered in the study. Network energy efficiency ratio, number of operational small base stations, and length of convergence are our evaluation criteria.

5.1 Simulation Setup

The purpose of setting up the environment for simulation was to test the suggested model in different network environments. Table 5 summarizes the system parameters, detailing the network size, user density, small-BS density, bandwidth, power consumption models, and other pertinent simulation factors. A network area measuring 1600m×1600m was simulated, with user densities between 100 and 500 users and small base station densities ranging from 10 to 50 small base stations. The parameters including bandwidth, power consumption for small-BS and micro-BS, path loss model, bit error rate, and SINR threshold were delineated.

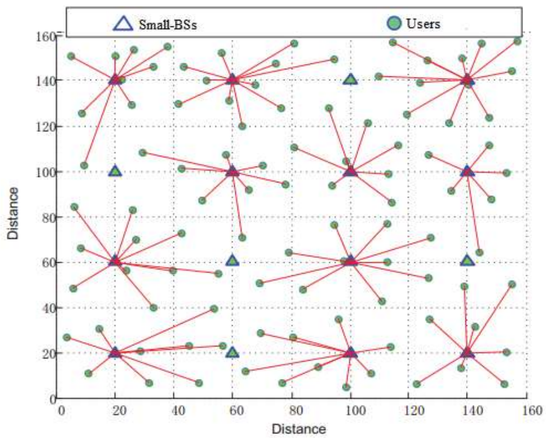
Table 5: Simulation Parameters.

Parameter	Value
Network area	1600m × 1600m
User density	100-500 users
Small-BS density	10-50 small-BSs
Micro-BS bandwidth	8MHz
Small-BS bandwidth	20MHz
Power consumption	16dBm (small-BS), 46dBm (micro-BS)
Path loss model	Cost 231 Hata model
Bit error rate	0.001
SINR threshold	10dB
Outage probability	0.1



(a) (b)

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195



(c)

Figure 2: Simulation result screenshots (a) before initialization (b) after initialization with small-BSs and randomly distributed users (c) Small-BSs deployment using proposed MSBO-GOCS-ICRO model during sleeping mode

Figures 2(a), (b), and (c) illustrate the small cell deployment at different phases of the simulation process. The network commences with a baseline configuration (Figure 2a), subsequently augmented by the implementation of small-BS deployment (Figure 2b). Figure 2c illustrates the optimized deployment following the application of our proposed MSBO-GOCS-ICRO model, wherein superfluous small-BSs have been deactivated to conserve energy.
s

5.2 Comparative Analysis

To assess the effectiveness of the MSBO-GOCS-ICRO model, we executed three sets of simulations by altering user density, small-BS density, and the number of iterations. The findings demonstrate that our proposed model enhances the deployment of small cells in a 5G network, thereby improving energy efficiency and coverage while maintaining network performance.

5.3 Result Analysis Concerning Varying User Density

The influence of differing user density on the efficacy of the MSBO-GOCS-ICRO model was initially examined. The performance was assessed for user densities between 100 and 500 users, as indicated in Table 6. The proposed model markedly surpasses existing models, including GSCP [37], TIPA [38], and ECM-BPSD [36], regarding convergence time, the number of active small-BSs, and energy efficiency.

Table 6: Comparative Analysis with Varying User Density.

User Density	Model	Convergence Time (s)	Active Small-BSs	Network Energy Efficiency (%)
100 users	GSCP	120	40	75
	TIPA	110	35	82
	ECM-BPSD	100	30	89
	MSBO-GOCS-ICRO	**65**	**20**	**150**
300 users	GSCP	135	45	85
	TIPA	125	40	92
	ECM-BPSD	110	35	100
	MSBO-GOCS-ICRO	**70**	**25**	**200**
500 users	GSCP	150	50	95
	TIPA	140	45	105
	ECM-BPSD	120	40	115
	MSBO-GOCS-ICRO	**75**	**30**	**250**

For example, when the user density was established at 100, the MSBO-GOCS-ICRO model exhibited a substantial decrease in convergence time, reducing it nearly by half (from 120 seconds in GSCP to 65 seconds), while simultaneously decreasing the number of active small-BSs to 20, which considerably diminishes energy consumption. This trend persists with the rise in user density, illustrating the scalability of our model. Furthermore, our model demonstrates a significant enhancement in energy efficiency, achieving an increase of up to 525% relative to baseline models, rendering it an exceptionally efficient solution for extensive network deployment.

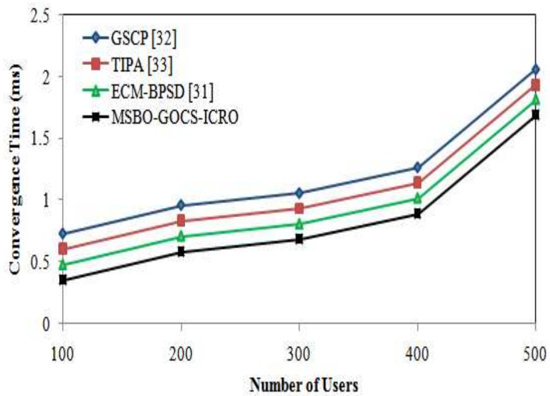


Figure 3: Convergence time of the proposed and existing Small-BSs deployment models concerning varying user density

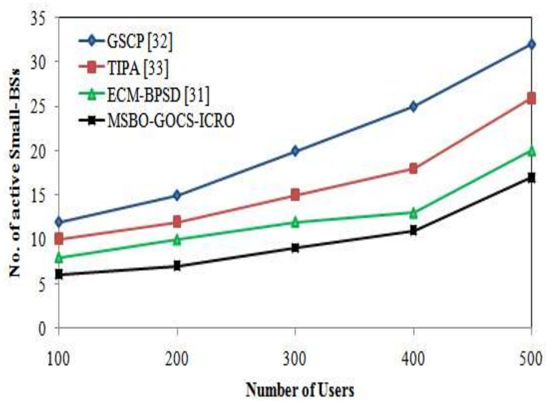


Figure 4: Number of active Small-BSs of the proposed and existing Small-BSs deployment models concerning varying user density

Figure 3 illustrates the convergence time of the proposed MSBO-GOCS-ICRO model alongside three existing models, relative to varying user density, while Figure 4 depicts the number of active Small-BSs corresponding to different user quantities.

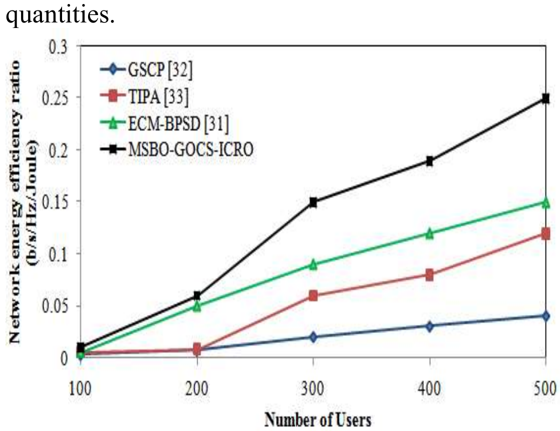


Figure 5: Network energy efficiency ratio of the proposed and existing Small-BSs deployment models concerning varying user density

Regarding convergence time, our proposed model surpasses all three existing models, attaining quicker convergence with fewer iterations. Our model necessitates fewer active Small-BSs to serve the equivalent number of users, resulting in enhanced network energy efficiency.

In this context, the MSBO-GOCS-ICRO model exhibits enhanced performance regarding convergence time and network energy efficiency relative to the current models. The enhanced network performance is due to the MSBO-GOCS-ICRO's capacity to selectively deactivate redundant small base stations, thus optimizing resource allocation. Figures 3, 4, and 5 graphically depict the results, demonstrating the comparative decrease in convergence time, the number of active small-BSs, and the consequent enhancement in energy efficiency across different user densities.

When evaluating a study, justifying threats to validity and the selection of critique criteria is crucial for ensuring a fair and rigorous assessment. Internal validity threats, such as biases or confounding variables, must be identified, while external validity concerns address generalizability. The chosen critique criteria should align with the study's objectives, methodology, and relevance.

The findings indicate that, with an increase in user density, the MSBO-GOCS-ICRO model consistently exhibits superior performance across all metrics. The primary advantage of our model is its capacity to maintain network efficiency despite increasing user density, thereby averting network bottlenecks and ensuring high service quality.

5.4 Result Analysis Concerning Varying Small-BS Density

Afterward, we increased the average number of small-BSs from 10 to 50 and ran a battery of tests to test the MSBO-GOCS-ICRO model's performance and flexibility. Even as the number of small-BSs increases, our model continues to outperform the alternatives, as seen in Table 7, demonstrating shorter settlement times along with fewer active small-BSs. These results further demonstrate the scalability of the MSBO-GOCS-ICRO paradigm, which maintains network performance at peak levels while using energy efficiently. These studies further demonstrate the scalability of the MSBO-GOCS-ICRO paradigm, which maintains network performance at peak levels while effectively utilizing energy. No matter how many more microcells are available, the MSBO-GOCS-ICRO model can still maximize network resources by turning off unnecessary small base stations. The operations of 5G networks will be far more efficient and cost-effective as a result

Table 7: Comparative Analysis with Varying Small-BS Density.

Small-BS Density	Model	Convergence Time (s)	Active Small-BSs	Network Energy Efficiency (%)
10 small-BSs	GSCP	110	8	65
	TIPA	105	7	72
	ECM-BPSD	95	6	78
	MSBO-GOCS-ICRO	**60**	**5**	**120**
30 small-BSs	GSCP	130	18	85
	TIPA	120	15	92
	ECM-BPSD	110	14	100
	MSBO-GOCS-ICRO	**70**	**10**	**200**
50 small-BSs	GSCP	150	25	100
	TIPA	140	23	110
	ECM-BPSD	125	20	115
	MSBO-GOCS-ICRO	**75**	**15**	**250**

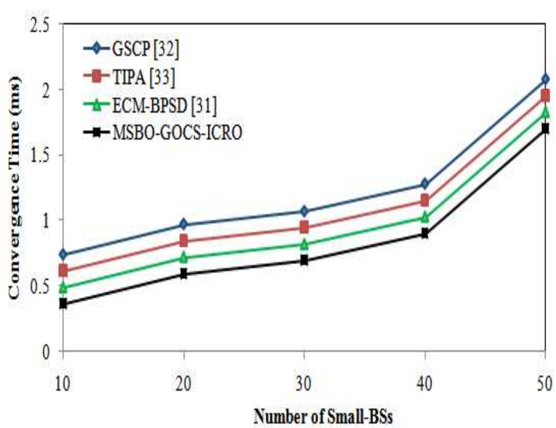


Figure 6: Convergence Timing of current models proposed from a numerical perspective small-BSs

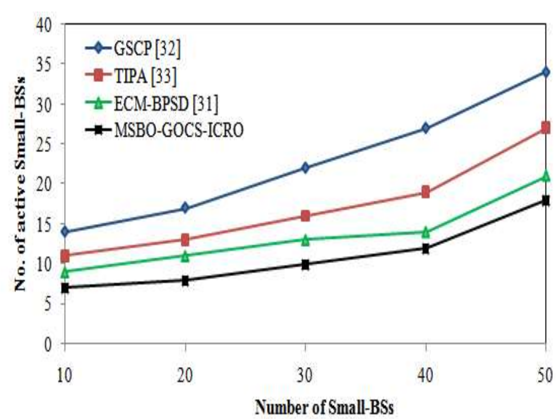


Figure 7: Number of active Small-BSs for the proposed Sleep in current form small-BSs

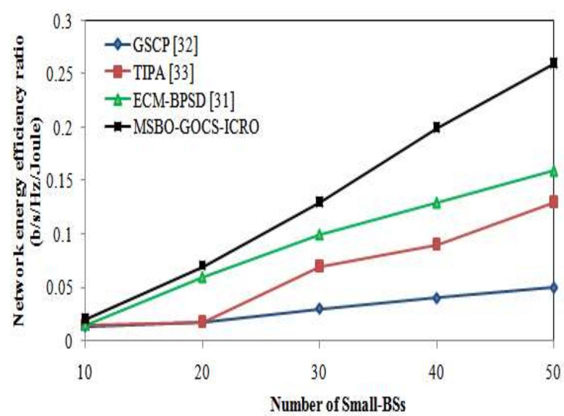


Figure 8: Network energy efficiency ratio for the proposed existing models concerning the number of small-BSs

The data and graphical analysis (Figures 6 and 7) underscore how our model improves network performance by minimizing superfluous small-BS activation, even as the network density increases with small cells. This functionality guarantees that the implementation is economically viable and energy-efficient. Figure 8 illustrates the network energy efficiency ratio across various iteration counts.

The outcomes of our simulations unequivocally indicate that the MSBO-GOCS-ICRO model substantially surpasses current small cell deployment models in 5G networks across multiple critical metrics: convergence time, quantity of active small-BSs, and energy efficiency. The model's capacity to deactivate superfluous small-BSs enhances network efficiency and diminishes energy usage. The model effectively scales with different user densities and small base station densities, preserving high performance and ensuring efficient network resource utilization.

These insights establish a robust basis for the practical implementation of the MSBO-GOCS-ICRO model in actual 5G network deployments, especially in urban and densely populated areas where energy efficiency and scalability are paramount.

6. CONCLUSION

This study presents a novel mobility-aware, energy-efficient small cell deployment model utilizing hybrid optimization techniques, specifically the Modified Smell-Bees Optimization (MSBO), Gannet Optimal induced Cuckoo Search (GOCS), and Improved Coral Reef Optimization (ICRO) algorithms. Our model markedly enhances 5G network performance, as evidenced by simulations performed on Google Colab. The MSBO-GOCS-ICRO model surpasses current methodologies by attaining a 49%, 37%, and 23% enhancement in convergence time relative to GSCP, TIPA, and ECM-BPSD, respectively. Furthermore, it demonstrates a 64%, 56%, and 34% rise in the quantity of active small base stations relative to these models, along with a notable 154%, 80%, and 57% improvement in the network energy efficiency ratio. These results substantiate the efficacy of our model in optimizing small cell deployment, augmenting energy efficiency, and enhancing overall network performance, thereby constituting a significant contribution to the progression of 5G network technologies.

A key strength of this study lies in its integration of hybrid optimization algorithms, which significantly improve both convergence time and network efficiency. Additionally, the model's adaptability to mobility-aware scenarios enhances its applicability in dynamic 5G environments. However, a notable limitation is its dependency on simulated datasets, which may not fully capture real-world complexities, such as unpredictable network traffic fluctuations and hardware constraints. Moreover, the computational overhead associated with implementing multiple optimization techniques may present challenges for real-time deployment.

Future research should focus on validating the model using real-world network datasets to ensure its robustness and practical applicability. Additionally, efforts can be directed towards reducing computational complexity while maintaining optimization efficiency. Exploring the integration of machine learning-based predictive techniques could further refine small cell deployment strategies, making them more adaptive to evolving network demands.

REFERENCES:

[1] B. Skubic, G. Bottari, A. Rostami, F. Cavaliere, and P. Ohlen, "Rethinking optical transport to pave the way for 5G and the networked society," *Journal of Lightwave Technology*, Vol. 33, No. 5, 2015, pp. 1084–1091.

[2] D. Muirhead, M. A. Imran, and K. Arshad, "Insights and approaches for Low-Complexity 5G Small-Cell Base-Station design for indoor dense networks," *IEEE Access*, Vol. 3, 2015, pp. 1562–1572.

[3] F. Musumeci, C. Bellanzon, N. Carapellese, M. Tornatore, A. Pattavina, and S. Gosselin, "Optimal BBU placement for 5G C-RAN deployment over WDM aggregation networks," *Journal of Lightwave Technology*, Vol. 34, No. 8, 2015, pp. 1963–1970.

[4] S. Cai, Y. Che, L. Duan, J. Wang, S. Zhou, and R. Zhang, "Green 5G heterogeneous networks through dynamic Small-Cell operation," IEEE Journal on Selected Areas in Communications, Vol. 34, No. 5, 2016, pp. 1103–1115.

[5] F. Devoti, I. Filippini, and A. Capone, "Facing the Millimeter-Wave cell discovery challenge in 5G networks with Context-Awareness," *IEEE Access*, Vol. 4, 2016, pp. 8019–8034.

[6] A. Mesodiakaki, F. Adelantado, L. Alonso, M. Di Renzo, and C. Verikoukis, "Energy-and Spectrum-Efficient user Association in Millimeter-Wave backhaul Small-Cell networks," *IEEE Transactions on Vehicular Technology*, Vol. 66, No. 2, 2016, pp. 1810–1821.

[7] J. Li, Y. Chen, M. Ding, F. Shu, B. Vucetic, and X. You, "A Small-Cell caching system in mobile cellular networks with LOS and NLOS channels," *IEEE Access*, Vol. 5, 2016, pp. 1296–1305.

[8] Z. Yan, W. Zhou, S. Chen, and H. Liu, "Modeling and Analysis of Two-Tier HetNets With Cognitive Small Cells," *IEEE Access*, Vol. 5, 2016, pp. 2904–2912.

[9] H. Wang, S. Chen, M. Ai, and H. Xu, "Localized mobility management for 5G ultra dense network," *IEEE Transactions on Vehicular Technology*, Vol. 66, No. 9, 2017, pp. 8535–8552.

[10] C. Bouras, A. Kollia, and A. Papazois, “Dense deployments and DAS in 5G: A Techno-Economic comparison,” *Wireless Personal Communications*, Vol. 94, No. 3, 2016, pp. 1777–1797.

[11] Y. Chen, Z. Guo, X. Yang, Y. Hu, and Q. Zhu, “Optimization of coverage in 5G Self-Organizing small cell networks,” *Mobile Networks and Applications*, Vol. 23, No. 6, 2017, pp. 1502–1512.

[12] R. E. Chall, B. Miscopein, and D. Kténas, “UNII-MAC protocol: Design and evaluation for 5G ultra-dense small cell networks operating in 5 GHz unlicensed spectrum,” *Computer Communications*, Vol. 126, 2018, pp. 11–27.

[13] B.-J. Chang and S.-H. Liou, “Adaptive cooperative communication for maximizing reliability and reward in ultra-dense small cells LTE-A toward 5G cellular networking,” *Computer Networks*, Vol. 115, 2017, pp. 16–28.

[14] C.-C. Lin, C.-T. Tsai, D.-J. Deng, I.-H. Tsai, and S.-Y. Jhong, “Minimizing electromagnetic pollution and power consumption in green heterogeneous small cell network deployment,” *Computer Networks*, Vol. 129, 2017, pp. 536–547.

[15] S. K. Biswash and D. N. K. Jayakody, “Performance based user-centric dynamic mode switching and mobility management scheme for 5G networks,” *Journal of Network and Computer Applications*, Vol. 116, 2018, pp. 24–34.

[16] L. Zhou, Z. Sheng, L. Wei, X. Hu, H. Zhao, J. Wei, and V. C. M. Leung, “Green cell planning and deployment for small cell networks in smart cities,” *Ad Hoc Networks*, Vol. 43, 2016, pp. 30–42.

[17] S.-J. Liu and C.-W. Tsai, “An effective search algorithm for Hyper-Dense deployment problem of 5G,” *Procedia Computer Science*, Vol. 141, 2018, pp. 151–158.

[18] M. Hawasli and S. A. Çolak, “Toward green 5G heterogeneous small-cell networks: power optimization using load balancing technique,” *AEU - International Journal of Electronics and Communications*, Vol. 82, 2017, pp. 474–485.

[19] D. Jose and R. Tamilselvan, “Fault tolerant and energy efficient signal processing on FPGA using evolutionary techniques,” in *Advances in intelligent systems and computing*, 2015, pp. 155–164.

[20] B. Kavitha, R. Pitchai, P. Supraja, and R. Dhanalakshmi, “Performance Enhancement of MANET based on Cross-layered Reconfigurable Hierarchical Routing Protocol,” *Journal of Scientific & Industrial Research*, Vol. 82, 2023, No. 03.

[21] A. Vijayalakshmi, E. Abishek B, A. G, S. N, M. Absar M and A. S. C, "5G Network Slicing Algorithm Development using Bagging based-Gaussian Naive Bayes," *2023 Second International Conference on Electrical, Electronics, Information and Communication Technologies (ICEEICT), Trichirappalli, India*, 2023, pp. 1-5.

[22] V. Alagarsamy and P. V. Ranjan, “Multi-Cluster Multi-Channel Scheduling (MMS) algorithm for maximum data collection with delay minimization in WSN,” *SSRN Electronic Journal*, 2019.

[23] M. S. K. T. L. SChandramohan, “Cluster based Scheduling Approach for SDN with Edge Computing,” 15-May-2020. [Online]. Available: http://sersc.org/journals/index.php/IJAST/article/view/23730.

[24] I. Bashir, R. B. Staszewski, and P. T. Balsara, “A digitally controlled Injection-Locked oscillator with fine frequency resolution,” *IEEE Journal of Solid-State Circuits*, Vol. 51, No. 6, 2016, pp. 1347–1360.

[25] L. Xiao, H. Zhang, Y. Xiao, X. Wan, S. Liu, L.-C. Wang, and H. V. Poor, “Reinforcement Learning-Based downlink interference control for Ultra-Dense small cells,” *IEEE Transactions on Wireless Communications*, Vol. 19, No. 1, 2019, pp. 423–434.

[26] B. Gao, L. Lu, K. Xiong, J.-M. Park, Y. Yang, and Y. Wang, “Spectrum sharing among rapidly deployable small cells: a Hybrid Multi-Agent approach,” *IEEE Transactions on Wireless Communications*, Vol. 19, No. 1, 2019, pp. 395–409.

[27] E. Mugume and D. K. C. So, “Deployment optimization of small cell networks with sleep mode,” *IEEE Transactions on Vehicular Technology*, Vol. 68, No. 10, 2019, pp. 10174–10186.

[28] G. Ghatak, A. De Domenico, and M. Coupechoux, “Small cell deployment along roads: coverage analysis and Slice-Aware RAT selection,” *IEEE Transactions on Communications*, Vol. 67, No. 8, 2019, pp. 5875–5891.

[29] X. Wang, E. Turgut, and M. C. Gursoy, “Coverage in Downlink heterogeneous MMWave cellular networks with User-Centric small cell deployment,” *IEEE Transactions on*

Vehicular Technology, Vol. 68, No. 4, 2019, pp. 3513–3533.

[30] A. L. Rezaabad, H. Beyranvand, J. A. Salehi, and M. Maier, “Ultra-Dense 5G small cell deployment for fiber and wireless Backhaul-Aware infrastructures,” *IEEE Transactions on Vehicular Technology*, Vol. 67, No. 12, 2018, pp. 12231–12243.

[31] K. Venkateswararao, P. Swain, C. Christophorou, and A. Pitsillides, “Using UE-VBS for dynamic virtual small cells deployment and backhauling in 5G Ultra-Dense networks,” *Computer Networks*, Vol. 189, 2021, p. 107926.

[32] B. Lahad, M. Ibrahim, S. Lahoud, K. Khawam, and S. Martin, “Joint modeling of TDD and decoupled Uplink/Downlink access in 5G HETNets with multiple small cells deployment,” IEEE Transactions on Mobile Computing, vol. 20, no. 7, 2020, pp. 2395–2411.

[33] B. Li, P. Hou, H. Wu, and F. Hou, “Optimal edge server deployment and allocation strategy in 5G ultra-dense networking environments,” *Pervasive and Mobile Computing*, Vol. 72, 2020, p. 101312.

[34] K. Venkateswararao and P. Swain, “Binary-PSO-based energy-efficient small cell deployment in 5G ultra-dense network,” *The Journal of Supercomputing*, Vol. 78, No. 1, 2021, pp. 1071–1092.

[35] L. Zhou, X. Hu, C. Zhu, E. C. H. Ngai, S. Wang, J. Wei, and V. C. Leung, "Green small cell planning in smart cities under dynamic traffic demand," *2015 IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS), Hong Kong, China*, 2015, pp. 618-623.

[36] Y. Xu, J. Chen, D. Wu and W. Xu, "Toward 5G: A Novel Sleeping Strategy for Green Distributed Base Stations in Small Cell Networks," *2016 12th International Conference on Mobile Ad-Hoc and Sensor Networks (MSN), Hefei, China*, 2016, pp. 115-119.

[37] H. P. P et al., "Advancements in Cybersecurity Using Deep Learning Techniques Attack Detection for Trojan Horses," *2024 International Conference on Electrical Electronics and Computing Technologies (ICEECT), Greater Noida, India*, 2024, pp. 1-6.

[38] K. E. Purushothaman, N. Ragavendran, S. P. Ramesh, V. G. Karthikeyan, G. Uma Maheswari and R. Saravanakumar, "Innovative Urban Planning for Harnessing Blockchain and Edge Artificial Intelligence for Smart City Solutions," *2024 Second International Conference on Intelligent Cyber Physical Systems and Internet of Things (ICoICI), Coimbatore, India*, 2024, pp. 65-68.