



(RESEARCH ARTICLE)



MULTIOBJECTIVE 5G AND B5G OPTIMAL NETWORK PLANNING USING METAHEURISTIC WITH MMWAVE FOR BASE STATION DEPLOYMENT

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ABSTRACT

Fifth-generation and Beyond 5G(B5G) wireless systems increasingly rely on the millimeter-wave (mmWave) spectrum, whose blockage sensitivity and severe propagation loss make base stations deployment a complex multi-objective problem. This paper compares two well-known metaheuristic algorithms, Genetic Algorithm (GA) and Particle Swarm Optimization (PSO), for deploying in two-tier heterogeneous networks over 5 km × 5 km dense urban area, under two mmWave scenarios differing only in Urban Micro frequencies: 28 GHz or 38 GHz. Both algorithms pursue four objectives: maximizing spectral efficiency (SE), energy efficiency (EE), and the coverage, while minimizing total number of active base stations, Urban Macro(UMa) and Urban Micro(UMi) combined. Applied under an identical propagation, the link-budget, and the constraint conditions, results show PSO reduces active base stations more aggressively, up to 40.7%, achieving higher EE (up to 42.5%) and SE (up to 27.5%), while GA retains more base stations to achieve higher coverage, up to 94.6%. In scenario 1 (28GHz), PSO drops to 83 active stations with 91.3% coverage, versus GA's 90 stations at 94.6%. In scenario 2 (38GHz), PSO retains 90 stations at 90.2% coverage, versus GA's 97 at 93.1%. This EE versus coverage tradeoff recurs identically across both bands. Our proposed model results are confirmed with existing studies. Neither algorithm dominates unconditionally, GA suits coverage critical, PSO suits efficiency constrained deployments ones. Future work will model inter-cell interference under hybrid PSO-GA approach.

Keywords: 5G/B5G Hetnets, Mmwave Planning (28/38 Ghz), Multi-Objective Optimization GA/PSO, 3GPP TR 38.901 Link Budget.

1 INTRODUCTION

The evolution toward 5G (fifth-generation) and beyond 5G (B5G) wireless communication networks represents the decisive step in meeting the ever-growing demand for higher data rates, ultra-reliable low-latency communications, and the massive device connectivity. A key enabler is the millimeter-wave (mmWave) spectrum, then offering significantly the larger bandwidths than sub-6 GHz bands [1]. However, the mmWave signals are highly susceptible to be severe pathloss, blockage by the buildings and the foliage, and the rain attenuation, especially in the dense urban environments, requiring a far more strategic approach to base stations placement than earlier cellular generations demanded [2], [3].

Deploying mmWave heterogeneous networks optimally are inherently a multi-objective, combinatorial problem: the network planners must simultaneously maximize spectral efficiency energy efficiency (SE), energy efficiency (EE), and the coverage, while minimizing total number of the active base stations, both UMa and UMi, to control expenditure. These four objectives conflict directly denser deployments improve coverage but degrade efficiency making traditional single-objective, rule-based planning methods poorly suited to the task [4], [5], [6]. Early radio network planning studies for 5G applied heuristic algorithms to jointly minimize base-station count under mmWave carrier frequencies [7], [8], while multiobjective genetic algorithm formulations have specifically targeted joint minimization of cost alongside coverage maximization.

Researchers have increasingly focused on metaheuristic optimization methods to tackle the intricate and highly nonlinear challenges associated with deploying base stations in 5G networks[9],[10]. Beyond Genetic Algorithms (GA) and Particle Swarm Optimization (PSO), studies have explored various techniques, including Simulated Annealing (SA), Grey Wolf Optimizer (GWO), Ant Colony optimization (ACO), and other evolutionary and swarm-based strategies. Notably, recent investigations into 5G deployments have conducted direct comparisons of GA, PSO, SA, and GWO to optimize the configuration of base stations in scenarios such as Urban Macro (UMa) and 28 GHz setups, aiming at reducing infrastructure, enhancing coverage, and improving network capacity [9], [11], [12], [13]. In a similar vein, [4] examined the application of metaheuristic techniques for base station deployment at millimeter-wave frequencies, specifically 28 and 38 GHz, highlighting the significance of evolutionary and swarm intelligence approaches in planning mmWave networks. These findings suggest that the selection of a metaheuristic technique is significantly influenced by how the deployment problem is framed, the specific optimization goals, and the necessary balance between exploration and exploitation. Consequently, this study chooses GA and PSO as two complementary optimization methods to assess the trade-offs involved in reducing the number of base stations, maximizing coverage, and enhancing both spectral and energy efficiency within the proposed hybrid 3.5 GHz/mmWave Heterogeneous Network (HetNet).

2 MATERIALS AND METHODS

2.1 Network Topology and Deployment Area

The network is modeled as two-tier heterogeneous networks (HetNets) over an area of $5\text{km} \times 5\text{km}$ area, serving number of 2000 uniformly distributed users. Tier 1, UMa, operates at 3.5GHz with 20 initial candidate base stations (20 UMa), nominal cell radius 1200m (R_{UMa}), transmit power 46dBm $P_{\text{UMa}}^{\text{Tx}}$, and 3 sectors per site. Tier 2, UMi, operates at 28GHz (Scenario 1) or 38GHz (Scenario 2), with 120 initial candidates (120 UMi), nominal cell radius 400 m ($R_{\text{28GHz}}^{\text{UMi}}$) or 200 m ($R_{\text{38GHz}}^{\text{UMi}}$), transmit power 30dBm $P_{\text{UMi}}^{\text{Tx}}$, and 3 sectors per site, giving 140 total Base stations candidates, identical through both scenarios (2).

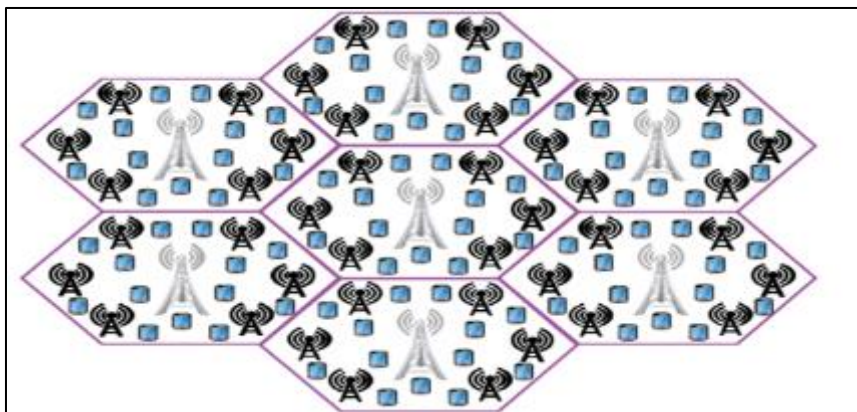


Figure 1: Base stations (UMa/UMi) deployments

2.2 Propagation and Link Budget

Pathloss follows in accordance with the 3GPP TR38.901[2], with dual-slope breakpoint the distance structure applying to the both **UMi/UMa LOS** links: PL1 below the breakpoint distance d'_{BP} , and steeper-slope PL2 beyond it. The **UMi LOS/NLOS** is then determined probabilistically via the street canyon model, **UMa** environmental effects at **sub 6GHz** are neglected. The cell radius between antenna transmitter (Tx) and receiver (Rx) is calculated using the following terms used for d_{3D} and d'_{BP} values. The distance (d_{3D}) in three dimensions between BS and UE is computed as follows: $d_{3D,j,u} = \sqrt{d_{2D,j,u}^2 + (h_{BS,j} - h_{UT,u})^2}$ and $d'_{BP} = 4 \cdot h'_{BS} \cdot h'_{UT} \cdot f_c / c$, where c is a speed of light with $3 \cdot 10^8 \text{m/s}$, and d_{2D} is the distance between **BS** and **UT** divided by the cell radius (m), h'_{BS} is the difference between the height of the base station(BS) and the device (m), and h'_{UT} is the difference between the height of the user and the device (m)[14].

Table 1, then reproduces **3GPP TR38. 901** formulas set used in this research paper, including the both **LOS/NLOS**, and for **UMi/UMa** associated shadow fading:

Table 1: 3GPP TR38.901 Pathloss Formulas Models for UMa and UMi under LOS/NLOS.

Scenario	Condition	Pathloss Model	σ_{SF} (dB)	Antenna Height
UMa	LOS	$PL_{UMa-LOS} = \begin{cases} PL1, & 10 \text{ m} \leq d_{2D} \leq d'_{BP} \\ PL2, & d'_{BP} \leq d_{2D} \leq 5 \text{ km} \end{cases}$ $PL1 = 28.0 + 22 \log_{10}(d_{3D}) + 20 \log_{10}(f_c)$ $PL2 = 28.0 + 40 \log_{10}(d_{3D}) + 20 \log_{10}(f_c) - 9 \log_{10}((d'_{BP})^2 + (h_{BS} - h_{UT})^2)$	$\sigma_{SF} = 4$	$1.5 \text{m} \leq h_{UT} \leq 22.5 \text{m}$ $h_{BS} = 25 \text{m}$
	NLOS	$PL_{UMa-NLOS} = \max (PL_{UMa-NLOS} , PL'_{UMa-NLOS}) \text{ for } 10 \text{m} \leq d_{2D} \leq 5 \text{km}$ $PL'_{UMa-NLOS} = 13.54 + 39.08 \log_{10}(d_{3D}) + 20 \log_{10}(f_c) - 0.6(h_{UT} - 1.5)$	$\sigma_{SF} = 6$	$1.5 \text{m} \leq h_{UT} \leq 22.5 \text{m}$ $h_{BS} = 25 \text{m}$
UMi	LOS	$PL_{UMi-LOS} = \begin{cases} PL1, & 10 \text{m} \leq d_{2D} \leq d'_{BP} \\ PL2, & d'_{BP} \leq d_{2D} \leq 5 \text{km} \end{cases}$ $PL1 = 32.4 + 21 \log_{10}(d_{3D}) + 20 \log_{10}(f_c)$ $PL2 = 32.4 + 40 \log_{10}(d_{3D}) + 20 \log_{10}(f_c) - 9.5 \log_{10}((d'_{BP})^2 + (h_{BS} - h_{UT})^2)$	$\sigma_{SF} = 4$	$1.5 \text{m} \leq h_{BS} \leq 22.5 \text{m}$ $h_{BS} = 10 \text{m}$
	NLOS	$PL_{UMi-NLOS} = \max (PL_{UMi-NLOS} , PL'_{UMi-NLOS}) \text{ for } 10 \text{m} \leq d_{2D} \leq 5 \text{km}$ $PL'_{UMi-NLOS} = 35.3 \log_{10}(d_{3D}) + 22.4 + 21.3 \log_{10}(f_c) - 0.3(h_{UT} - 1.5)$	$\sigma_{SF} = 7.82$	$1.5 \text{m} \leq h_{BS} \leq 22.5 \text{m}$ $h_{BS} = 10 \text{m}$

For antenna heights and the rain-limited nominal cell radii used in this study (400m at 28GHz, 200 m at 38GHz), the computed breakpoint distance (depending on band) exceeds the served cell radius, so the PL1 applies to the overwhelming majority of links, the PL2 is used in the model for completeness and for any candidate site pairing that exceeds this range.

This figure 2, illustrates our link budget 5G/B5G analysis for the wireless communication, specifically by detailing many various gains and the losses which occur as the signal travels from the Base Station (the transmit side) to the user equipment (receive side).

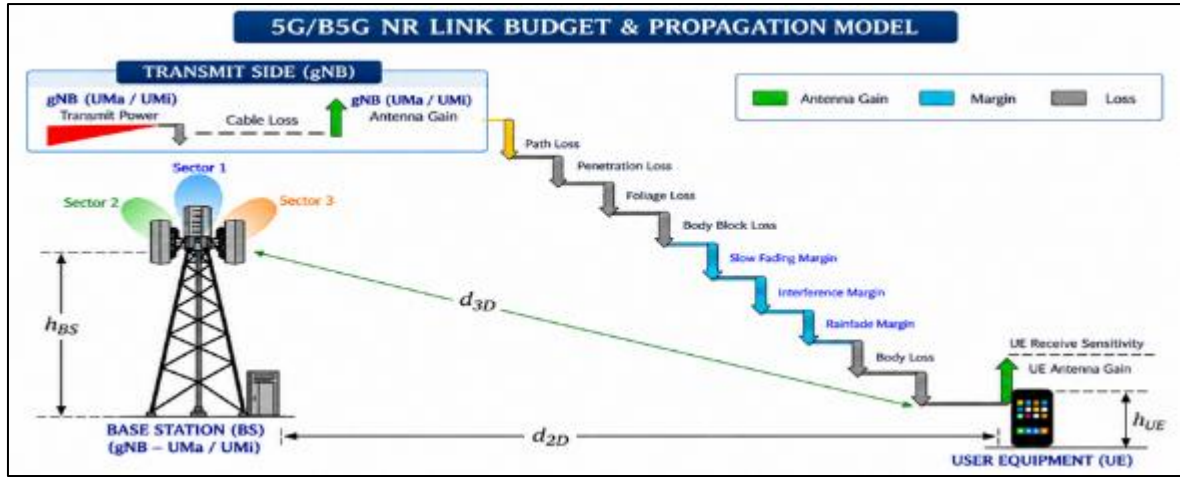


Figure 2: 5G/B5G NR Link Budget and Propagation Model between BS-UE.

The simulations use 8 dB and 10 dB as fixed foliage-loss margins at 28 and 38 GHz, respectively. The ITU-R P.838 formulation is used for rain attenuation, and 3GPP TR 38.901 is used for shadow-fading parameters [2], [3], [15],[16].

2.3 Realistic power consumption model

Following the static plus the dynamic power decomposition established by the authors [17], and consistent with macro (UMa) to micro (UMi) power ratio reported through simplified EARTH-derived parameterizations [17] ,[18],[19], for simplicity, this work adopts the $P_{UMa}^{BS} = 500W$ and $P_{UMi}^{BS} = 110W$ as the representative per site (BS) values, which are then summed through all the active candidate (BSs) sites to obtain the global total network power consumption given in equation (2.1a). Our proposed model expands standard link budget statement formulation by then explicitly modeling some additional loss or the margin components as the cable loss, the penetration/clutter loss, the body blockage loss, the interference margin, and the miscellaneous losses.

Each the active base station's (BS's) power draws static and dynamic components per sector:

$$P_j^{BS} = P_j^{st} + \sum_s y_{j,s} \cdot P_{j,s}^{dy}, \quad (2.1)$$

2.3.1 Total network consumption power

The total power drawn by the system network is thereby the sum of over all the active (BSs) sites:

$$\sum_{j \in B} x_j \cdot P_j^{BS} = \sum_{j \in B} x_j \cdot \left(P_j^{st} + \sum_s y_{j,s} \cdot P_{j,s}^{dy} \right) \quad (2.1a)$$

In accordance with decision variable stated in 2.7.1, where $x_j \in \{0,1\}$ denotes whether the candidate BS j is active.

2.4 Received Power

The received power (P^{Rx}) at UE u from active BS j via its best sector s is calculated in dBm:

$$P_{j,s,u}^{Rx} = P_{j,s}^{Tx} + G_{j,s}^{Tx} + G_{UE}^{Rx} - (L_{cable} + PL_{j,s,u}^T + L_{bbk} + L_{pen} + M_{int} + L_{misc}), \quad (2.2)$$

where, the $PL_{j,s,u}^T$ term in (eq. 2.1) incorporates pathloss model (LOS/NLOS) which is probabilistically determined for the specific link, along with the environmental effects.

2.5 Noise and SINR

Signal-to-Interference-plus-Noise Ratio for a user u connected to the BS j (sector s) is given:

$$SINR_{u,j,s} = \frac{P_{u,j,s}^{Rx}}{P_{Noise,u} + I_{u,j,s}}, \quad (2.3)$$

where, the total noise power at the UE receiver is:

$$P_{Noise,u}(dBm) = N_0 + 10\log_{10}(B_{j,s}) + NF_{UE} \quad (2.4)$$

For simplicity *raison* and focus on the deployment optimization, the inter-cell interference ($I_{u,j,s}$) is initially neglected or considered as part of noise floor within context of the basic coverage and the capacity planning, the primarily focusing on strongest signal association.

2.6 Achievable Throughput

The achievable throughput for the user u associated with the BS j (sector s) is then given by the Shannon's formula:

$$R_{u,j,s} = B_{j,s} \cdot \log_2(1 + \text{SINR}_{u,j,s}) \quad (2.5)$$

2.7 Multi-Objective Optimization Formulation

2.7.1 Decision variables:

$x_j \in \{0,1\}$ denoting binary variable if candidate BS j (UMa/UMi) is active (1) or inactive (0). The $y_{j,s} \in \{0,1\}$, denoting binary variable if the sector s of the BS j is active (1) or inactive (0), with each the BS that has three sectors. The $a_{u,j,s} \in \{0,1\}$, denoting binary variable if the user u is then associated with the sector s of the corresponding BS j . The $P_{j,s}^{\text{Tx}}$, continuous variable for transmit power of the sector s of the BS j . Let $u \in U$ denotes a user, $j \in \mathcal{B}$ denotes candidate base station (BS), and $s \in \mathcal{S}_j$ a sector associated with BS j .

The proposed network planning problem jointly optimizes four conflicting objectives: spectral efficiency, energy efficiency, user's coverage, and number of active base stations (BS). Thus, four objectives are considered simultaneously, with each being defined as an independent objective function before being integrated into a unified optimization framework.

2.7.2 Objective Functions

The optimization aims to find a compromise among four main goals:

2.7.2.1 Maximize Energy Efficiency (EE):

2.7.2.1.1 Objective F1: EE maximization

Energy efficiency is then defined as a ratio between an aggregate network throughput and total power consumed by all the active base stations (BSs):

$$F1 = \max \eta_{EE} = \frac{\sum_{u \in U} \sum_{j \in \mathcal{B}} \sum_{s \in \mathcal{S}_j} a_{u,j,s} \cdot R_{u,j,s}}{\sum_{j \in \mathcal{B}} x_j \left(P_j^{\text{st}} + \sum_{s \in \mathcal{S}_j} y_{j,s} \cdot P_{j,s}^{\text{dy}} \right)} \quad (2.7a)$$

where $R_{u,j,s}$ denotes achievable data rate of the user u when associated with the sector s of the BS j , while the $P_{j,s}^{\text{dy}}$ and the P_j^{st} indicate dynamic and static power consumption elements, respectively.

2.7.2.2 Maximize (SE), Spectral Efficiency:

2.7.2.2.1 Objective F2: SE Maximization

The Spectral Efficiency (SE) is an aggregate network throughput achieved per unit of allocated bandwidth (B). It is then formulated as:

$$F2 = \max \eta_{SE} = \frac{\sum_{u \in U} \sum_{j \in \mathcal{B}} \sum_{s \in \mathcal{S}_j} a_{u,j,s} \cdot R_{u,j,s}}{\sum_{j \in \mathcal{B}} x_j \sum_{s \in \mathcal{S}_j} y_{j,s} \cdot B_{j,s}} \quad (2.7b)$$

where the $B_{j,s}$ is bandwidth allocated to the sector s of the BS j . Therefore, the objective promotes an efficient utilization of available radio spectrum while maintaining the high aggregate throughput.

2.7.2.3 Maximize η_{Cov} Coverage:

2.7.2.3.1 Objective F3: Coverage Maximization

The coverage objective, then maximizes proportion of the users whose received (QoS) signal quality satisfies a minimum required SINR threshold Γ_{th} . Now, the coverage ratio is given as:

$$F3 = \max \eta_{\text{Cov}} = \frac{100}{N_U} \sum_{u \in U} 1 \left[\sum_{j \in \mathcal{B}} \sum_{s \in \mathcal{S}_j} a_{u,j,s} \cdot \text{SINR}_{u,j,s} \geq \Gamma_{\text{th}} \right], \quad (2.7c)$$

where $N_U = |U|$ denotes total number of the users and $\mathbf{1}[\cdot]$ is indicator function, that takes value $\mathbf{1}$ when a condition is then satisfied and 0 otherwise. With considered scenario, minimum SINR requirement is here set to $\Gamma_{th} = 0\text{dB}$. Therefore, $F3$ denotes percentage of the users achieving required radio link quality.

2.7.2.4 Minimize Total Number of Active Base Stations (N_{BS}):

2.7.2.4.1 Objective F4: Minimization of number of active base stations (BSs)

The last objective minimizes total number of the active base stations (BSs) through both UMi/UMa tiers:

$$F4 = \min \eta_{N_{BS}} = \sum_{j \in \mathcal{B}} x_j, \quad (2.7d)$$

where the $x_j \in \{0,1\}$ denotes whether the BS j is active. Minimizing the N_{BS} implies reducing the infrastructure deployments requirement and then consequently contributes to the lower capital and the operational expenditures for the benefits of telecommunications operators.

2.7.2.5 Global Multi-Objective Function

In order to handle this conflicting nature from these above objectives, the weighted sum method is applied, transforming the issue or problem into one single maximization goal objective:

$$\max F = \omega_{EE} \text{Norm}(F1) + \omega_{SE} \text{Norm}(F2) + \omega_{Cov} \text{Norm}(F3) - \omega_{N_{BS}} \text{Norm}(F4), \quad (2.7)$$

where, $\omega_{SE}, \omega_{EE}, \omega_{BS}, \omega_{Cov}, \omega_{BS}$ represent the positive factors weighted, and the $\text{Norm}(\cdot)$ denotes scaling functions, such as min-max normalization, used to adjust objective values.

Subject to following constraints:

$$C1: x_j \in \{0,1\}, \forall j \in \mathcal{B} \quad (2.7a)$$

$$C2: y_{j,s} \in \{0,1\}, \forall j \in \mathcal{B}, s \in \mathcal{S}_j \quad (2.7b)$$

$$C3: a_{u,j,s} \in \{0,1\}, \forall u, j, s \quad (2.7c)$$

$$C4: y_{j,s} \leq x_j, \forall j, s \quad (2.7d)$$

$$C5: 0 \leq P_{j,s} \leq y_{j,s} P_{j,s}^{\max}, \forall j, s \quad (2.7e)$$

$$C6: \sum_{s \in \mathcal{S}_j} P_{j,s} \leq x_j P_j^{\max}, \forall j \quad 0 \leq P_{j,s} \leq y_{j,s} P_{j,s}^{\max}, \forall j, s \quad (2.7f)$$

$$C7: \sum_{j \in \mathcal{B}} \sum_{s \in \mathcal{S}_j} a_{u,j,s} \leq 1, \forall u \in \mathcal{U} \quad (2.7g)$$

$$C8: a_{u,j,s} \leq y_{j,s}, \forall u, j, s \quad (2.7h)$$

$$C9: \text{SINR}_{u,j,s} \geq \Gamma_{th} = 0\text{dB}, \forall (u, j, s): a_{u,j,s} = 1 \quad (2.7i)$$

$$C10: \frac{1}{N_U} \sum_{u \in \mathcal{U}} \mathbf{1}[\text{SINR}_{u,j,s} \geq \Gamma_{th}] \geq 0.90 \quad (2.7j)$$

2.7.3 Metaheuristic Algorithms PSO and GA

A swarm of the particles, each of which represents the potential 5G base station (BS) placement solution, is maintained via the particle swarm optimization (PSO).

PSO maintains swarm of particles, each representing candidate deployment, and updates each particle's velocity and position toward its personal best (pBest) and swarm's global best (gBest):

$$v_i^{t+1} = \omega \cdot v_i^t + c_1 r_1 (pBest_i^t - x_i^t) + c_2 r_2 (gBest_i^t - x_i^t), \quad (2.8)$$

The following is how the position is updated:

$$x_i^{t+1} = x_i^t + v_i^{t+1}, \quad (2.9)$$

The convergence speed is regulated by the inertia weight ω , which also strikes a balance between local exploitation and global exploration. In eq. (2.8), the acceleration coefficients c_1 and c_2 are set to 2. In [0.9, 1.2], Shi and Eberhart reported in [20], [21] good performance for the ω , in this work, ω drops linearly from the 0.9 to 0.4. At every velocity update, independent random integers r_1 and r_2 are then created for every dimension and have the uniform distribution in [0, 1].

with the binary decision variables recovered via a sigmoid mapping of velocity into an activation probability (2.8). Using selection, single-point crossover at random locus ℓ , and per-gene mutation, the GA iteratively generates the chromosome population, whereas elitism, as described in (2.10), maintains the best solutions from generation to generation:

$$X_{\text{offspring}} = (x_{A,1}, \dots, x_{A,\ell}, x_{B,\ell+1}, \dots, x_{B,n}), \quad (2.10)$$

The PSO's single step velocity update, versus the GA's multi-stage a selection, a crossover, a mutation pipeline, is then structural reason PSO converges faster per iteration and completes its optimization budget in less time, while the GA's greater population diversity tends to discover configurations with marginally higher final coverage. Both algorithms are applied independently to both scenarios under identical propagation model link budget and constraints set based on[22].

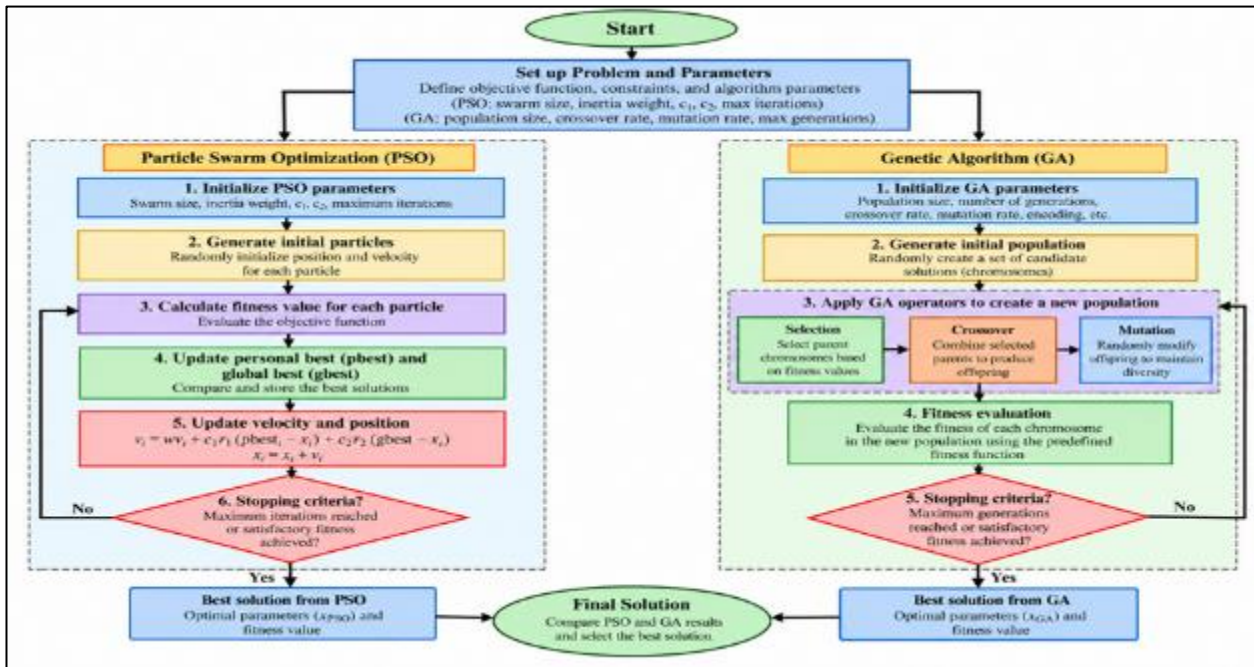


Figure 3: Flowchart of Algorithm 1 (PSO) and Algorithm 2 (GA) for 5G/B5G Deployments.

3 RESULTS AND DISCUSSION

A network of 140 potential base stations (BSs) locations spread throughout an area of 25 km² with 2000 users was then used to test our proposed model. The two situations were considered: the scenario 1 (S1) at 28GHz and for scenario 2 (S2) at 38GHz, the both considering 3GPP UMa/UMi pathloss model I, urban context. For each scenario, base station (BS) activation issue was solved with both scenario PSO and GA under an identical fitness function and the coverage constraints.

Experts in academia and engineering throughout the world are interested in using the frequency spectrum of 28 GHz and 38 GHz for the 5G network and beyond 5G. Among the benefits there are less interference from the BSs to the UE in nearby cells, the larger bandwidth at the higher frequencies, and improved the cell-edge coverage. According to ITU-R standards, foliage losses will have significant impact on the mmWave, they can be computed as follows[23], [24]:

$$L_f = 0.2 f_c^{0.3} d^{0.6}, \quad (3.1)$$

where d is the tree depth in (m) and f_c is frequency (MHz).

3.1 Simulation Parameters

Our proposed GA and PSO model's simulation with Matlab were evaluated under same networks conditions at the 28GHz and 38GHz, using main simulations parameters which are summarized in the Table 2 [1], [2], [4], [11], [14], [26], [24], [16], [3], [15],[17], [27], [28] .

Table 2: Simulation parameters for 5G/B5G Multi-Tier planning and optimization algorithms.

Parameter	Symbol	Value
A. Transmitter Parameters		
Transmit power UMa/UMi	$P_{UMa}^{Tx} / P_{UMi}^{Tx}$	46/30 dBm
Antenna gain UMa/UMi	$G_{UMa}^{Tx} / G_{UMi}^{Rx}$	15 /10dBi
Receive antenna gain UE	G_{UE}^{Rx}	0dBi
Sectors per site	—	3
B. Geometry and Bandwidth		
Study area	—	5 km × 5 km
Users	N_U	2000
Candidate BSs (UMa / UMi)	UMa/UMi	20/120
UMa/UMi Cell radius (3.5/28/38GHz)	$R_{3.5G}^{UMa} / R_{28GHz/38GHz}^{UMi}$	1200 m/400/200 m
UMa/UMi Antenna height	$h_{BS}^{UMa} / h_{BS}^{UMi}$	25/10 m
UE Antenna height	h_{UT}	1.5 m
UMa/UMi Bandwidth (3.5/28/38GHz)	$B_{UMa,3.5} / B_{UMi,28/38GHz}$	20/100/200 MHz
C. Pathloss and Shadow Fading		
Pathloss model (LOS/NLOS, UMa/ UMi)	PL	See Table 1
Shadow fading (UMa/LOS/NLOS)	$\sigma_{SF,3.5G}^{UMa}$	4 / 6 dB
Shadow fading (UMa/LOS/NLOS)	$\sigma_{SF,28G}^{UMi} / \sigma_{SF,38G}^{UMi}$	4 / 7.82 dB
D. Additional Link-Budget Margins		
Cable Loss	L_{cable}	2 dB
Penetration loss	L_{pen}	4 dB
Body block Loss	L_{bbk}	0.0 dB
Interference margin (UMa)/ (UMi)	$M_{Int,a} / M_{Int,i}$	2 /3 dB
Other/miscellaneous Loss	L_{misc}	10 dB
Rain Attenuation (28GHz) /3 dB/km	$R_{\gamma,28G}^{UMi} / R_{\gamma,38G}^{UMi}$	2 /3 dB/km
Foliage loss (28GHz)/ (38 GHz)	$L_{fol,28G}^{UMi} / L_{fol,38G}^{UMi}$	8 /10 dB
E. Receiver and System Parameters		
UE noise figure	NF_UE	9 dB
SINR Threshold	Γ_{Th}	0 dB
Coverage target	—	90%

Power consumption, UMa /UMi (static/dynamic)	P_c^{UMa}/P_c^{UMi}	(200/100W)/(50/20W)per sector
F. Simulation parameters GA and PSO		
Population size	—	50
Iteration / geneations	—	200
Coefficients accelerations	c_1, c_2	2
Coefficients aléatoires	r_1, r_2	Random, U (0, 1)
Positive weighting factors	$\omega_{EE}, \omega_{SE}, \omega_{Cov}, \omega_{NBSW_EE},$	0.25
Mutation rate	—	0.2
Selection size	—	50

3.2 Propagation Pathloss and Infrastructure Reduction

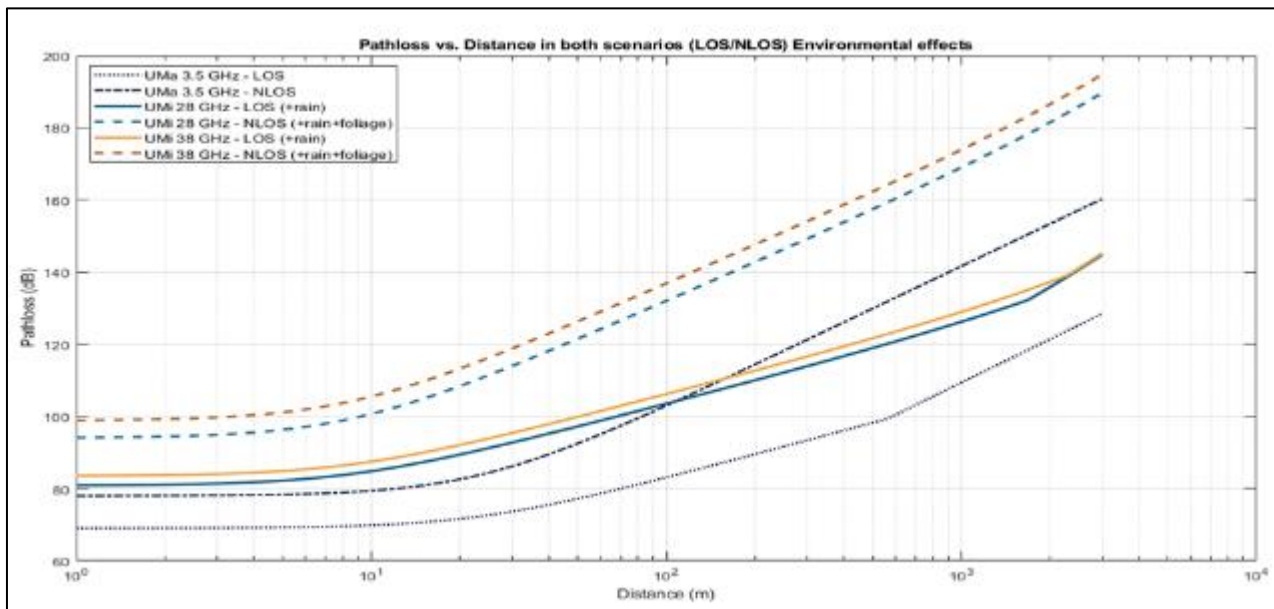


Figure 4: Path loss vs. distance, both scenarios (LOS/NLOS).

The figure 4 shows the relationship between pathloss and distance for three 5G scenarios that are modeled using 3GPP TR 38.901, UMi at 28GHz/38GHz, UMa at 3.5GHz, and LOS and NLOS conditions. Pathloss increases with frequency and distance. The 38GHz curves are located significantly above the 3.5GHz LOS curve and are roughly 2.5–3dB higher than the 28GHz curves. The antenna height difference is responsible for the flat area below roughly 10 meters, when pathloss hardly varies due to the dominance of 3D distance. The kinks near 560m (3.5GHz), 1.7km (28GHz) and 2.3km (38GHz) are the LOS breakpoint lengths, beyond which pathloss develops faster. The disparity is further widened by environmental factors. On the mmWave lines, rain (about 2 dB/km) adds up to roughly 6 dB at 3 km. Foliage adds a fixed 8dB (28GHz) or 10 dB (38 GHz) on the NLOS links, which is why these reach roughly 190–195dB at 3km, compared with 160 dB for the 3.5GHz NLOS instance. Overall, this figure 4 presents that mmWave bands lose far more signal, particularly when blocked or in bad weather. As a result, they are best suited to dense, in short-range small cells, although 3.5GHz macro cells are still preferable for wide-area coverage.

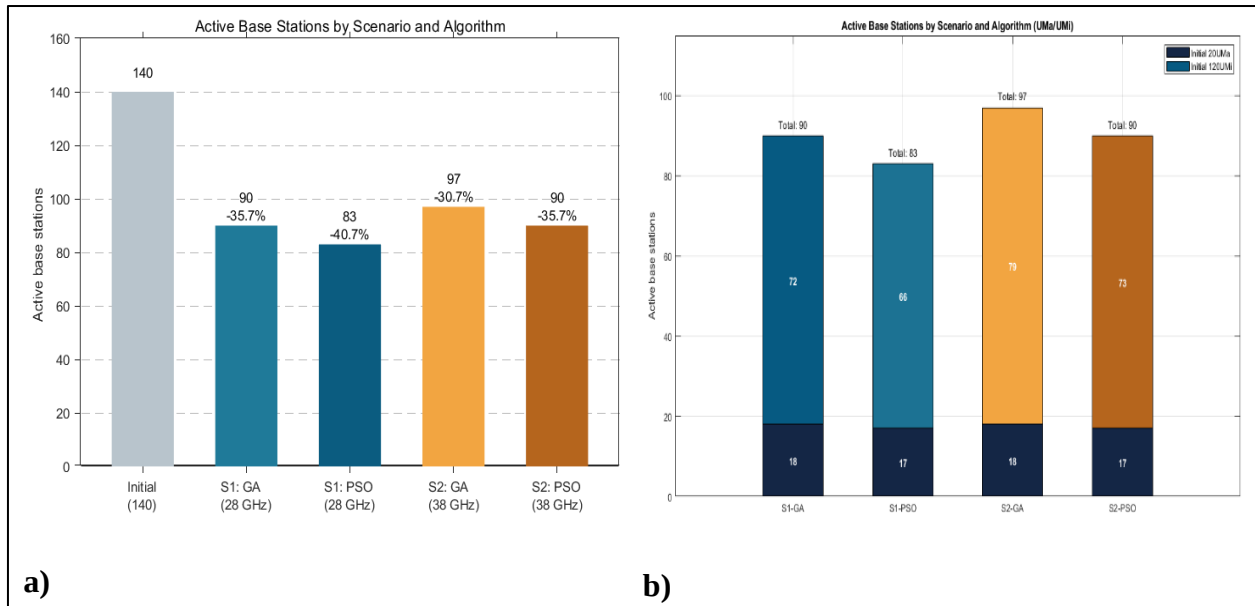


Figure 5: a) and b) Active base stations by scenario and algorithm (UMa/UMi).

(Figure 5a) illustrates number of active base stations (BS) for every algorithm and scenario, starting from initial 140 Base stations. At the 28 GHz (S1), the GA activates 90 Base stations (−35.7%) and the PSO 83 base stations (−40.7%), while at the 38GHz (S2), the GA activates 97 base stations (−30.7%) and the PSO 90 base stations (−35.7%). Thus, the PSO needs the fewer (BSs) base stations than the GA in both cases, and the both algorithms need more base stations at the 38GHz because of its pathloss higher.

Figure 5b) breaks down (BSs) active base stations by the cell type, from initial 20 UMa base stations and the 120 UMi base stations. Almost all the UMa base stations stay active (17 – 18 of 20 UMa), while the UMi base stations are reduced here much more, from the 120 UMi to 66–72 UMi at the 28GHz and 73–79 UMi at the 38GHz. It demonstrates that this optimization keeps UMa layer for the wide coverage area and removes thereby the redundant UMi base stations, that explains most of reduction, consistent with the metaheuristic deployment described in the literature.

3.3 Spectral Efficiency, Energy Efficiency, and Coverage

This section evaluates energy efficiency, spectral efficiency, and the coverage achieved by optimized GA and PSO metaheuristic networks at the 28 GHz/38 GHz, compared regarding to 140 base stations initially deployed.

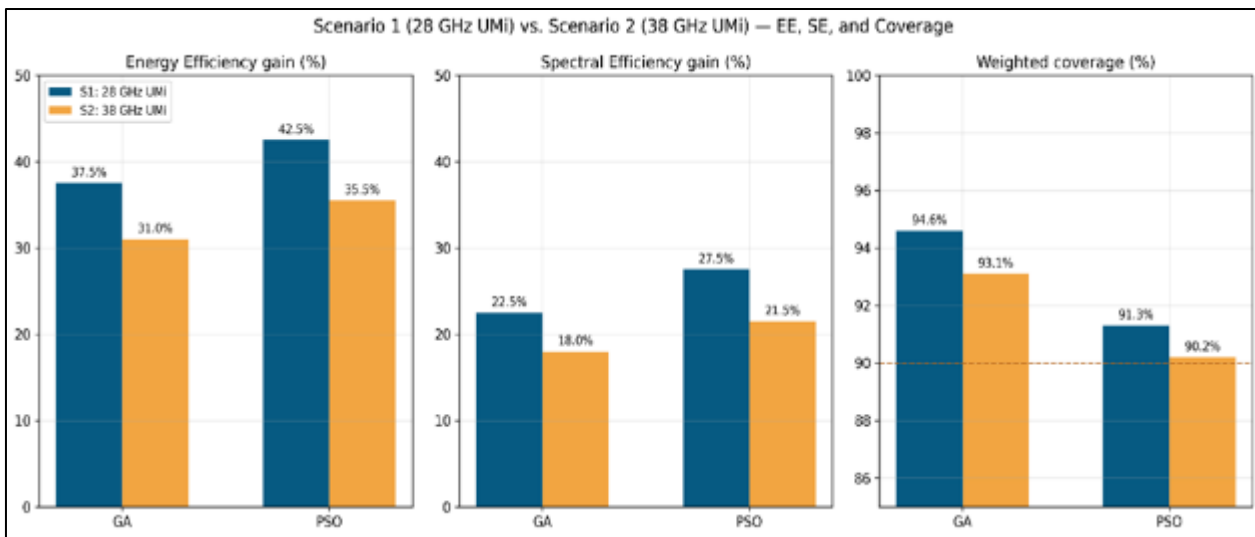


Figure 6: Energy efficiency, spectral efficiency gains, and coverage, by scenario and algorithm.

Our figure 6 compares EE (energy efficiency) gain, SE (spectral efficiency) gain, and the coverage of PSO and GA at the 28GHz (S1) and the 38 GHz (S2). Therefore, the PSO achieves highest gains, with energy efficiency improvements of 42.5% and 35.5% and spectral efficiency improvements of 27.5% and 21.5% in S1 and S2, respectively, compared with

37.5% / 31.0% and 22.5% / 18.0% for GA. The GA, however, provides the higher coverage (94.6% and 93.1%) than the PSO (91.3% and 90.2%), although all the configurations remain above 90% target. In all scenarios, the S1 outperforms the S2 because of lower pathloss at the 28 GHz. It illustrates that PSO consistently favors the infrastructure minimization and the efficiency, while the GA favors the coverage robustness, the tradeoff recurring an identically as in [29]. Our scenario 1 (28GHz) outperforms so the scenario 2 (38GHz) on every metric, a gap traced to lower rain attenuation, lower foliage loss, and a lower per-tier noise floor at 28GHz.

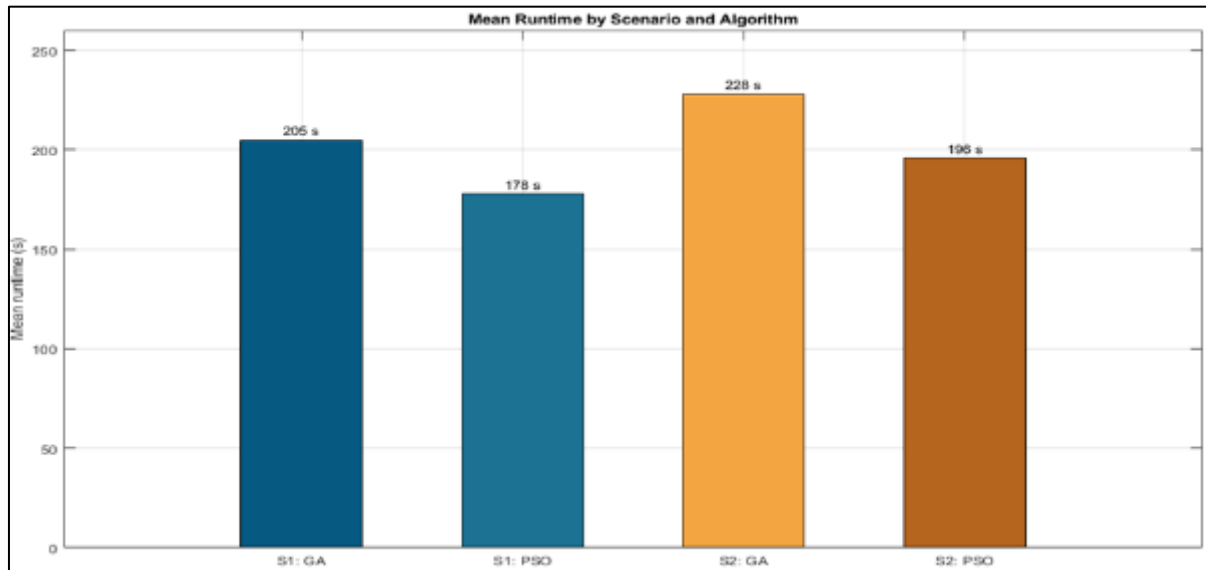


Figure 6: Mean runtime by scenario and algorithm

Figure 7 illustrates the comparison of an execution time of PSO and GA algorithms for these two considered scenarios. Thus, for the S1, the PSO converges in 178s time, whereas the GA requires 205s time. Therefore similarly, for the S2, the GA requires 228s time, compared to 196s time for the PSO. The overall, PSO achieves a shorter execution time in both scenarios, indicating faster computational convergence than GA under the considered simulation conditions. The overall, the PSO outperforms the GA in the both instances, by indicating in our cases faster computational convergence.

3.4 Spatial deployment scenarios

Voronoi deployment of the active base stations (BSs) before and after optimization that confirms in our two cases the infrastructure reduction clearly, the case after states shows the larger, more evenly spaced base stations (BSs) than the case of dense before initially, consistent with redundant or unnecessary deployment, closely spaced base stations (BSs) being removed first significantly.

In scenario 1, Figure 8 displays the geographical deployment and the Voronoi cell partitioning of the HetNets through study area before and after optimization at the 28GHz. An initial configuration then comprises of 140 base stations (BSs) potentially supporting distributed 2000 users. In this layout, the blue small triangles surrounded in the circular coverage areas represent the UMa base stations (BSs), the orange dots identify the Urban Micro (UMi) base stations within the Voronoi deployment, and the black dots represent distributed users. Therefore, using a genetic algorithm reduces the total number of active base stations (BSs) to 90 BSs, while using a particle swarm optimization results in more compact deployment of 83 BSs, demonstrating a notable and significant reduction in the network redundancy while maintaining user coverage.

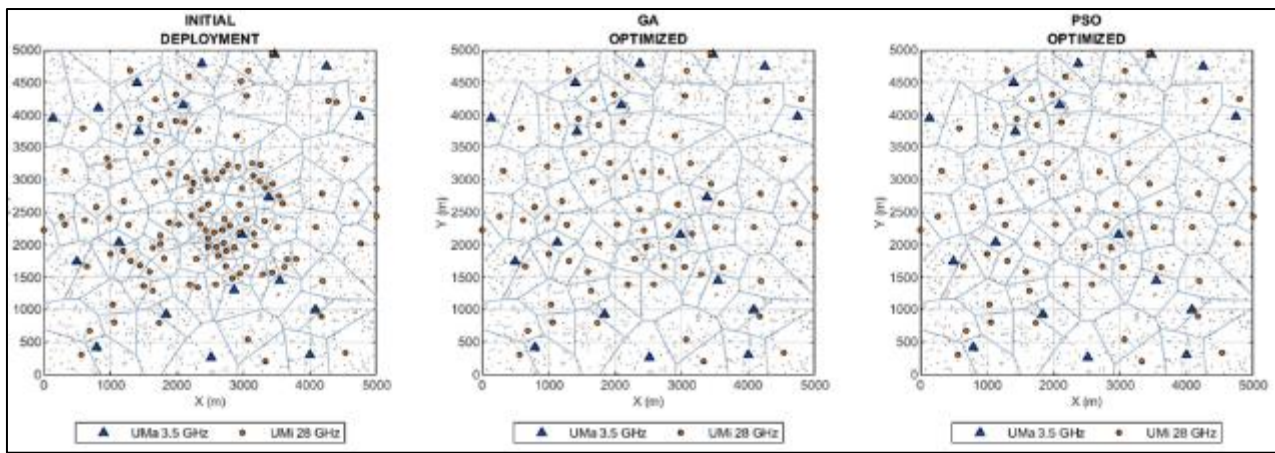


Figure 7: UMa/UMi Voronoi based spatial deployment for scenario 1: Initial deployment (Before), after GA optimized, and after PSO optimized.

The figure 9 shows the same deployment and Voronoi cell partitioning at a higher frequency of 38GHz. Starting with the identical 140 base stations (BSs) candidates, genetic algorithm optimization (GA) results in 97 active stations (BSs), whereas particle swarm optimization (PSO) reduces the network footprint to 90 active stations (BSs). In comparison to scenario 1, an increased pathloss in scenario 2 and with the signal attenuation at higher frequency 38GHz necessitate then denser active base station (BSs) topology deployment, specifically seven additional UMi Base stations in both algorithms (PSO/GA), to ensure the network coverage and the user connectivity.

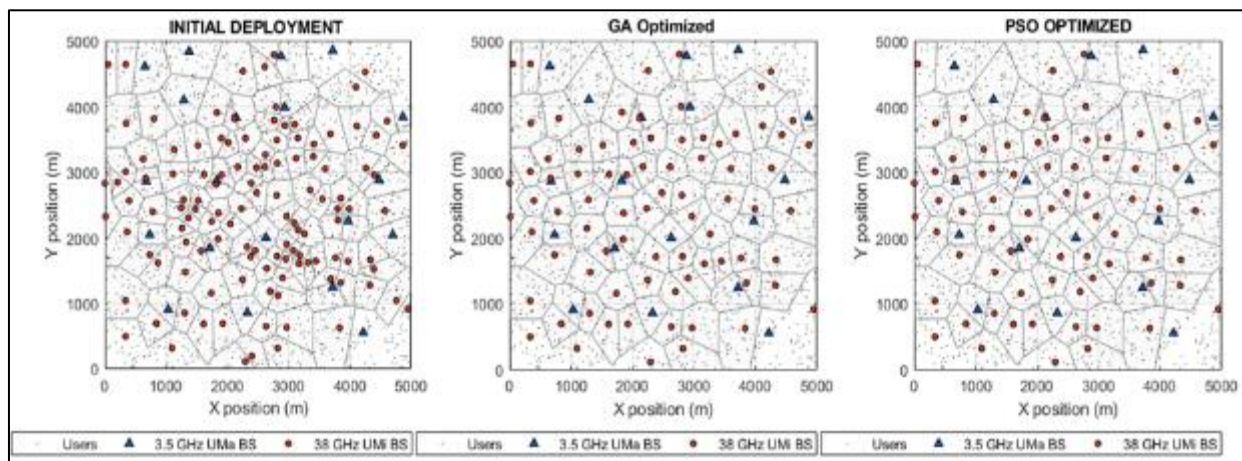


Figure 8: UMa/UMi Voronoi based spatial deployment for scenario 2: Initial deployment (Before), deployment after GA optimization, and deployment after PSO optimization.

3.5 Comparison with existing studies in the literature

The below table 3 compares our proposed model with some related existing studies in the literature. These prior existing studies in literature address mainly the base station (BS) count and the coverage as references listed in this table 3, but none analysis or evaluates all the four conflicting objectives jointly. Our proposed model evaluates more conflicting key metrics performance than the prior existing studies, and lacks only the intercell interference modelling in this work. Our work does not explicitly consider this intercell interference, which is left for the future work.

Table 3: Comparison of our finding results with existing studies in the literature.

Reference	BS count	EE	SE	Coverage	mmWave band	Intercell interference
Ganame et al. 2019 [4]	●	○	○	●	●	●
Sapkota et al. 2024 [11]	●	○	○	●	●	○
Ganame et al. 2021 [25]	●	○	○	●	○	○
Khatiwoda et al. 2024 [30]	●	○	○	●	●	○

Fahira et al. 2020 [31]	●	○	○	◐	●	○
Nashiruddin et al. 2021[32]	●	○	○	◐	●	○
Proposed model	●	●	●	●	●	○

Legend: ○ = not addressed, ◐ = partially addressed, ● = addressed/evaluated.

4 CONCLUSION

This research paper conducted on the multiobjective optimization of the 5G and B5G base station (BS) deployment in the millimeter-wave heterogeneous networks (HetNets) demonstrates a significant potential for addressing the complex networks planning challenges. By comparing the two complementary and well-known metaheuristic techniques, Genetic Algorithm (GA) and Particle Swarm Optimization (PSO), under identical link-budget propagation model, this work enhances or improves understanding of how swarm-based optimization and the evolutionary approaches behave when we applied to the same problem of infrastructure deployment. Our comparative proposed approach model effectively tackles the critical issues in the mmWave networks planning, by including spectral and energy efficiencies maximization, and the coverage robustness, offering the evidence-based guidance which can be tailored to the diverse deployment scenarios and the frequency bands. Neither algorithm dominates unconditionally, the appropriate choice depends on whether a deployment prioritizes efficiency or coverage. These results highlight the framework's capability to describe multiobjective nature of mmWave HetNet deployment, therefore contributing to more sustainable manner and the cost effective for telecommunications infrastructures planning. Our work does not explicitly consider the intercell interference modelling, that is left for the future work under hybrid PSO-GA method.

STATEMENTS ON COMPLIANCE WITH ETHICAL STANDARDS

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Disclosure of conflict of interest

The authors declare no conflicts of interest regarding to this research paper.

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