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Optimized beamforming and network slicing for dense urban 5G deployments

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Key words

Beamforming;
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Optimization;
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Abstract

Optimizing beamforming and network slicing is critical for enhancing spectral efficiency, energy efficiency, and resource distribution fairness in dense urban 5G networks. This paper proposes a hybrid genetic algorithm particle swarm optimization (GA-PSO) method to jointly optimize beamforming weights, bandwidth allocation, and power distribution, balancing computational efficiency with near optimal performance. The hybrid approach uses GA for global exploration and PSO for fast convergence, overcoming the limitations of standalone heuristic and exact optimization methods. Simulation experiments in a dense urban 5G network with massive MIMO base stations show that proposed method achieves up to 15% higher spectral efficiency and 18% better energy efficiency compared to existing integer linear programming (ILP) method, while significantly reducing computational complexity. Convergence analysis further confirms that the hybrid method requires fewer iterations to reach near-optimal solutions, making it suitable for real-time 5G resource management. Additionally, fairness evaluation using Jain's Index shows that proposed method ensures more equitable resource distribution than conventional methods. These results establish hybrid GA-PSO method as an effective and scalable solution for next-generation wireless networks.

Introduction

The rapid growth of 5G networks has transformed wireless communication, enabling ultra-high data rates, massive connectivity, and low-latency services (Akhtar et al. 2020, Mughees et al. 2021). Urban environments, characterized by high user density and mobility, pose significant challenges in ensuring efficient spectrum utilization and reliable communication links (Ahamed and Faruque 2021, You et al. 2021). To address these challenges, advanced techniques such as beamforming and network slicing have emerged as key enablers of enhanced network performance (Wang et al. 2022, Han et al. 2024). Beamforming uses multiple antennas to direct signals toward specific users, improving signal strength and mitigating interference (Beiranvand et al. 2023). Meanwhile, network slicing allows dynamic resource partitioning to cater for diverse service which includes Ultra-Reliable Low-Latency Communication (URLLC), enhanced Mobile Broadband (eMBB) and massive Machine-Type Communication (mMTC) (Pokhrel et al. 2020, Wang et al. 2021, Abuyaghi et al. 2025, Geranmayeh and Grass 2025). Despite the advantages of beamforming and slicing, several technical challenges persist in dense urban 5G deployments. High user mobility leads to frequent handovers and dynamic user positioning, causing variations in beam alignment and slice allocation (Wang et al. 2021, You et al. 2021). Multi-cell interference further complicates spectral efficiency, requiring robust coordination among base stations to mitigate signal degradation (Poirot et al. 2020, Boutiba et al. 2023). Additionally, the fluctuating demand for different slices necessitates intelligent and adaptive resource allocation mechanisms to ensure service quality (Alameddine et al. 2021). Computational complexity remains a major bottleneck, as traditional optimization methods often struggle with real-time processing under dynamic network conditions (Ullah et al. 2022, Wang et al. 2022, Yuan et al. 2023).

To address these challenges, this paper proposes an optimization-based framework for jointly optimizing beamforming and network slicing in high-mobility, dense urban environments. While machine learning approaches have gained traction in beamforming and slicing, they require extensive training datasets, high computational resources, and may lack generalization to unseen scenarios (Alkhateeb et al. 2018, Brilhante et al. 2023). In contrast, optimization-based methods, particularly Integer Linear Programming (ILP) (Boutiba et al. 2023, Fayad et al. 2023), game theory (Yang et al. 2017, Tran and Le 2020), and metaheuristic algorithms (Poirot et al. 2020, Gomes et al. 2022), provide structured, mathematically rigorous solutions that can efficiently adapt to real-time network conditions. ILP and game theory enable precise formulation of beamforming as a constrained optimization problem, ensuring spectral and energy efficiency. Additionally, metaheuristic approaches, such as Genetic Algorithms (GA) (Fayad and Cinkler 2024) and Particle Swarm Optimization (PSO) (Archi and Gunawan 2020, Shami et al. 2022), offer fast, near-optimal solutions for beam selection and

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slice allocation under dynamic conditions. This paper presents an integrated optimization framework for beamforming and network slicing in urban 5G networks. The main contributions include ILP based beamforming optimization model that maximizes signal to interference noise power ratio (SINR) while minimizing power consumption. Furthermore, a game-theoretic network slicing strategy based on a stackelberg game is proposed to ensure fairness and efficient resource allocation among competing slices (Amasyali et al. 2020). Additionally, a hybrid metaheuristic approach combining GA and PSO is introduced for real-time joint beamforming and slicing optimization. The proposed methods are evaluated through simulations, comparing their performance against existing heuristic techniques in terms of spectral efficiency, energy efficiency and computational complexity. The remainder of the paper is organized as follows: The next section reviews related work on beamforming and network slicing. This is followed by a presentation of the system model and assumptions, leading to the formulation of the optimization problem. The proposed ILP, game-theoretic and metaheuristic approaches are then introduced. Performance evaluation based on simulation results is subsequently provided. Finally, the paper concludes with key findings and potential directions for future research.

Related work

The integration of beamforming and network slicing has been widely explored in 5G networks, with researchers proposing various optimization techniques, machine learning approaches, and heuristic methods to enhance spectral and energy efficiency (Akhtar et al. 2020, Pokhrel et al. 2020, You et al. 2021, Jin et al. 2023,). Beamforming is a critical technology in massive MIMO systems, improving signal quality and reducing interference through directed transmission (Koc and Le-Ngoc 2021, Yuan et al. 2023). Early works focused on fully digital beamforming, leveraging precoding techniques such as zero-forcing (ZF) and minimum mean square error (MMSE) to maximize SINR (Kebede et al. 2022, Ullah et al. 2022). However, these methods suffer from high computational complexity, making them impractical for real-time urban scenarios with high user mobility (Kebede et al. 2022). To mitigate this, hybrid beamforming has been proposed, reducing hardware complexity by combining analog and digital beamforming techniques (Wang et al. 2022). Alkhateeb et al. (2018) demonstrated that hybrid precoding significantly improves energy efficiency while maintaining spectral performance, but their study did not account for dynamic mobility patterns and interference fluctuations in dense urban environments (Mozaffariahrar et al. 2022).

More recent research has explored machine learning-based beamforming, where deep reinforcement learning and neural network models predict optimal beam configurations (Brilhante et al. 2023). For instance, Boutiba et al. (2023) applied deep reinforcement learning to beam selection, achieving faster adaptation to channel variations. However, these methods require extensive training datasets and may struggle with generalization under unseen mobility scenarios (Beiranvand et al. 2023). Alternative optimization-based methods, such as ILP, provide structured, mathematically rigorous solutions for beam selection, as demonstrated by Fayad et al. (2023). While ILP based approaches offer high precision, they face scalability challenges when applied to large-scale 5G networks with dynamic user distributions (Ejaz and Choudhury 2025). Network slicing has emerged as a key enabler of 5G flexibility, allowing operators to allocate virtualized resources tailored to diverse service requirements (Pokhrel et al. 2020, Alameddine et al. 2021, Yang et al. 2023). Traditional slicing methods rely on static resource partitioning, leading to inefficient spectrum utilization under fluctuating traffic conditions (Hsiao et al. 2021). Dynamic slicing approaches, leveraging game theory, reinforcement learning, and metaheuristic algorithms, have been proposed to optimize slice allocation in real time (Yan et al. 2023).

Game-theoretic models, such as the stackelberg game and coalition formation game, have been employed to model interactions between network slices and infrastructure providers (Rathi and Gupta 2020, Awada et al. 2023). Amasyali et al. (2020) proposed a stackelberg-based resource allocation strategy that balances network utility and fairness. However, game-theoretic methods often rely on predefined utility functions, which may not fully capture real-time traffic dynamics in urban deployments (Mughees et al. 2021). Meanwhile, reinforcement learning-based approaches, such as the work by Alkhateeb et al. (2018), enable adaptive slicing decisions based on past observations. While effective, these models require extensive training, limiting their deployment in rapidly changing environments (Komba et al. 2024).

Metaheuristic algorithms, including Genetic Algorithms (GA) and PSO, have gained traction due to their ability to find near-optimal slicing strategies with lower computational overhead (Wang et al. 2021). Archi and Gunawan (2020) demonstrated the effectiveness of GA-PSO hybrid models in maximizing throughput and minimizing latency. However, existing studies primarily focus on static or low-mobility scenarios, neglecting the impact of high-speed mobility and frequent handovers in dense urban areas (Akhtar et al. 2020). While beamforming and network slicing have been extensively studied in isolation, their joint optimization remains an open challenge (You et al. 2021). Current approaches either optimize beamforming independently and then allocate slices or use heuristic-based joint allocation schemes with suboptimal performance (Elgarhy et al. 2024). Few studies have explored mathematical optimization for integrating these two technologies in high-mobility environments. Beiranvand et al. (2023) proposed a convex optimization framework for joint beamforming and slicing, achieving improved network efficiency. However, their model assumed static channel conditions, limiting its applicability in dense urban scenarios. Meanwhile, Yan et al. (2023) introduced a deep learning-based joint optimization scheme, but their approach required extensive offline training and lacked adaptability to real-time conditions. Recent works suggest that combining ILP for beamforming with game-theoretic or metaheuristic slicing approaches could provide a more balanced tradeoff between accuracy and scalability

(Fayad et al. 2023), yet no comprehensive framework has been proposed to date.

Existing solutions for beamforming optimization rely on computationally expensive digital beamforming or data-intensive machine learning models that lack adaptability to dynamic environments (Brilhante et al. 2023). Similarly, network slicing techniques using static or game-theoretic approaches fail to fully optimize real-time resource allocation in high-mobility dense urban areas (Mozaffariahrar et al. 2022). Moreover, the joint optimization of beamforming and slicing remains largely unexplored in the context of dense urban deployments, where user mobility and interference management are critical challenges. This paper addresses these gaps by proposing an optimization-based framework that integrates ILP based beamforming, game-theoretic slicing, and metaheuristic hybrid approaches. By leveraging integer linear programming for structured beam selection, a stackelberg game for dynamic slice allocation, and a GA-PSO hybrid model for computational efficiency, the proposed approach aims to enhance spectral and energy efficiency in dense urban 5G networks.

Materials and Methods

System model

In this work a dense urban 5G network is considered, composed of multiple macro, micro and femto cells base stations (BSs), each equipped with a massive MIMO array. A schematic of this arrangement is shown in Figure 1. The network serves a mix of static and mobile users, categorized into different network slices based on their service requirements. The architecture integrates beamforming at the BSs to improve spectral efficiency and network slicing to dynamically allocate resources across multiple service types, including eMBB, URLLC and mMTC. Network slice 1, 2 and 3 are optimized for eMBB, URLLC and mMTC, respectively.

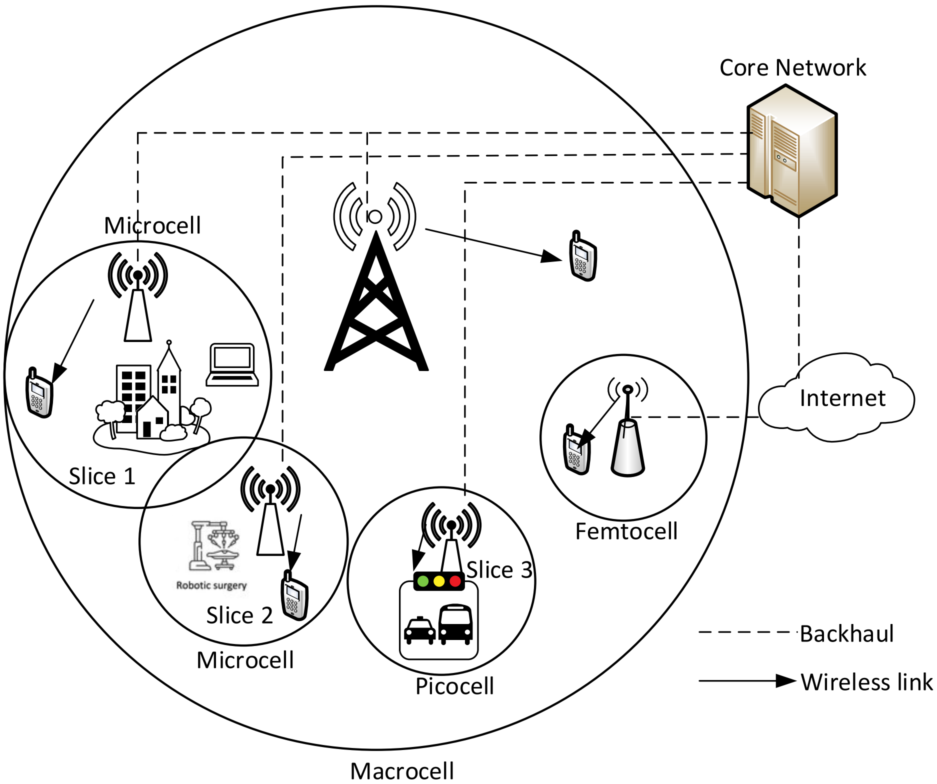

Figure 1: Illustration of Network Slicing in 5G Network

A multi-cell massive MIMO system is considered where each BS, indexed by $b \in ß$, is equipped with M antennas and serves multiple single-antenna users, indexed by $u \in U$. Each user belongs to one of the three slices and is served with a dedicated beamforming vector. The total system bandwidth B_{total} is divided among the slices, ensuring their respective quality of service (QoS) constraints.

Each BS transmits a signal $\mathbf{x}_b \in \mathbb{C}^{M\mathrm{x}1}$ given by

$$\mathbf{x}_b = \sum_{u \in U_b} \mathbf{F}_b \mathbf{W}_b \mathbf{v}_u \mathbf{s}_u \tag{1}$$

where
$\mathbf{F}_b \in \mathbb{C}^{M x N_{RF}}$ is the analog beamforming matrix (RF precoder)
$\mathbf{W}_b \in \mathbb{C}^{N_{RF} x U}$ is the digital beamforming matrix
$\mathbf{v_u} \in \mathbb{C}^{U x 1}$ is the precoded symbol vector for user *u*
$\boldsymbol{s}_u \sim \mathcal{CN}(0,1)$ is the unit-power transmitted data symbol for user *u*
N_{RF} is the number of RF chains
The wireless channel follows an independent Rayleigh fading model with coefficients presented as

$$\mathbf{h}_{b,u} \sim \mathcal{CN}\left(0, \mathbf{R}_{b,u}\right) \tag{2}$$

where $\mathbf{h}_{b,u} \in \mathbb{C}^{M x 1}$ represent the channel vector from b^{th} BS to user u and $\mathbf{R}_{b,u}$ is the spatial correlation matrix. In this study uncorrelated Rayleigh fading is assumed which is translated as $\mathbf{R}_{b,u} = \beta_{b,u} \mathbf{I}_M$ where $\beta_{b,u}$ captures large-scale fading(path loss and shadowing) and $\mathbf{I}_M$ denotes identity matrix of dimension *M x M*.
The received signal at user *u* is given as

$$y_u = \mathbf{h}_{b,u}^H \mathbf{x}_b + \sum_{k \neq u} \mathbf{h}_{b,u}^H \mathbf{x}_k + n_u \tag{3}$$

.

$$y_u = \mathbf{h}_{b,u}^H \sum_{u \in U_b} \mathbf{F}_b \mathbf{W}_b \mathbf{v}_u \mathbf{s}_u + \sum_{k \neq u} \mathbf{h}_{b,u}^H \sum_{k \in U_b} \mathbf{F}_b \mathbf{W}_b \mathbf{v}_k \mathbf{s}_k + n_u \tag{4}$$

where $n_u \sim \mathcal{CN}(0, \sigma^2)$ is the additive white Gaussian noise (AWGN).

QoS Analysis and Backend Queuing

Each slice has different quality of service (QoS) requirements, influencing resource allocation. The eMBB users require high data rates with relaxed latency constraints. The URLLC users need ultra-low latency with strict reliability constraints. The mMTC users demand massive connectivity with low individual data rates. The backend system introduces queuing delays due to resource contention. In this work, service time per user is modeled using an M/M/1 queue, where the total latency for user is:

$$D_u = \frac{1}{\mu_u - \lambda_u} \tag{5}$$

where μ_u is the service rate and λ_u is the arrival rate. The total delay must satisfy

$$D_u + D_{trans,u} \leq D_{\max,u} \tag{6}$$

This ensures that each user meet its QoS requirements.

The signal to interference plus noise ratio (SINR) for user *u* is defined as

$$SINR_u = \frac{\left|\mathbf{h}_{b,u}^H \mathbf{F}_b \mathbf{W}_b \mathbf{v}_u\right|^2}{\sum_{k \neq u} \left|\mathbf{h}_{b,u}^H \mathbf{F}_b \mathbf{W}_b \mathbf{v}_k\right|^2 + \sigma^2} \tag{7}$$

Using Shannon's capacity formula, the achievable data rate for user *u* is given as

$$R_u = B_{u,j} \log_2\left(1 + SINR_u\right) \tag{8}$$

where $B_{u,j}$ is the dynamically allocated bandwidth for user u within slice *j*.

Network Slicing and Resource Allocation

Each slice dynamically allocates resources based on user demand, ensuring efficient use of power and bandwidth. While the focus of this work is on high-level resource allocation, it is acknowledged that 5G resource blocks (PRBs) and transmission time intervals (TTIs) play a fundamental role in practical implementation. PRBs, which consist of 12 subcarriers in a 180 kHz bandwidth, are dynamically allocated in each TTI of 0.5 ms duration. The PRBs are not modeled explicitly in this study, the total bandwidth B_j allocated to slice *j* represents the sum of PRBs assigned to that slice over time.
The power allocated to each user P_u is proportional to its beamforming gain and SINR, presented as:

$$P_u = \eta.\frac{\left|\mathbf{h}_{b,u}^H \mathbf{F}_b \mathbf{W}_b \mathbf{v}_u\right|^2}{\sum_{k\neq u}\left|\mathbf{h}_{b,u}^H \mathbf{F}_b \mathbf{W}_b \mathbf{v}_k\right|^2 + \sigma^2} \quad 9$$

where η is a normalization factor ensuring power constraints are met. The bandwidth allocation follows an adaptive scheme

$$B_{u,j} = \frac{B_{total}\cdot\sum_{u\in S_j} R_u}{\sum_{j=1}^{N}\sum_{u\in S_j} R_u} \quad 10$$

The bandwidth allocation in equation 10 ensures fairness among users and slices. Therefore, the objective is to optimize beamforming and network slicing for spectral efficiency, interference minimization and QoS assurance, presented as

$$\begin{gathered}\max_{\mathbf{F}_b,\mathbf{W}_b,B_{u,j},\mathbf{P}_u} \sum_{u\in U} R_u \\ \text{s.t} \quad \sum_{u\in U_b} P_u \le P_{\max}, \forall b \in B \\ \sum_{j=1}^{N}\sum_{u\in S_j} B_{u,j} \le B_{total} \\ SINR_u \ge \gamma_u, \forall_u \in U \\ D_u + D_{trans,u} \le D_{\max.u} \\ P_u \ge 0, B_{u,j} \ge 0\end{gathered} \quad 11$$

where γ_u is the minimum threshold SINR for user *u*.

The problem in equation 11 is non-convex and should be solved using convex approximations, game theory and metaheuristic algorithms.

Problem Formulation

Convex Approximation

The optimization problem formulated in equation 11 is designed to maximize the sum rate R_u across all users while ensuring QoS constraints on SINR, power, and delay. However, the objective function is non-convex due to the fractional SINR expressions and coupled beamforming variables. To address this, the convex approximations are applied, including semi-definite relaxation (SDR) and successive convex approximation (SCA). Since the objective function is expressed as

$$\max_{\mathbf{F}_b,\mathbf{W}_b,B_{u,j},\mathbf{P}_u} \sum_{u\in U} B_{u,j}\log_2\left(1+SINR_u\right) \quad 12$$

The focus is on making SINR constraints convex while incorporating dynamic QoS thresholds.
Since the original SINR constraint is given as

$$\frac{\left|\mathbf{h}_{b,u}^H \mathbf{F}_b \mathbf{W}_b \mathbf{v}_u\right|^2}{\sum_{k\neq u}\left|\mathbf{h}_{b,u}^H \mathbf{F}_b \mathbf{W}_b \mathbf{v}_k\right|^2 + \sigma^2} \ge \gamma_u \quad 13$$

The expression in equation 13 is non-convex due to the quadratic terms in both numerator and denominator. If Charnes-Cooper transformation (Chen et al. 2005) is applied, defining an auxiliary variable t_u as

$$t_u = \frac{1}{\sum_{k\neq u}\left|\mathbf{h}_{b,u}^H \mathbf{F}_b \mathbf{W}_b \mathbf{v}_k\right|^2 + \sigma^2} \quad 14$$

and multiplying both sides by t_u, the new linearized constraint is obtained expressed as

$$\left|\mathbf{h}_{b,u}^H \mathbf{F}_b \mathbf{W}_b \mathbf{v}_u\right|^2 .t_u \ge \gamma_u \quad 15$$

Since t_u remains nonlinear, the first-order Taylor expression is used to approximate it at iteration *i* as

$$t_u^{(i+1)} = t_u^{(i)} - \frac{\left(t_u^{(i)}\right)^2}{\sum_{k\neq u}\left|\mathbf{h}_{b,u}^H \mathbf{F}_b \mathbf{W}_b \mathbf{v}_k\right|^2 + \sigma^2} \quad 16$$

This iterative approach ensures convergence to a near-optimal convex solution. Instead of using fixed SINR thresholds, adaptive QoS constraints is defined based on traffic demand and latency budgets as

$$\gamma_u = \alpha_j . \gamma_{\min} + (1-\alpha_j) . \gamma_{\max} \tag{17}$$

where α_j is a traffic load-dependent weighting factor defined as

$$\alpha_j = \frac{\lambda_u}{\sum_{u \in S_j} \lambda_u} \tag{18}$$

This ensures real-time resource adaptation based on network congestion. The delay constraint linking SINR and transmission latency is introduced as

$$D_{trans,u} = \frac{1}{\log_2(1+SINR_u)} \le D_{\max,u} \tag{19}$$

Applying Jensen's inequality, the $\log_2(1+x)$ can be approximated as

$$\log_2(1+x) \le \frac{x}{\ln(2)} \tag{20}$$

which simplifies the latency constraint to

$$\frac{1}{SINR_u} \le D_{\max,u} . \ln(2) \tag{21}$$

The formulation in equation 21 enables latency-aware power and bandwidth allocation in designated network slices shown in Figure 1.

It should further be noted that to enforce beamforming matrix constraint, the $\mathbf{W}_b$ must be positive semi-definite as

$$\mathbf{W}_b \succ 0 \tag{22}$$

A more restrictive condition involves bounding eigenvalues of $\mathbf{W}_b$ to control power distribution

$$\lambda_{\min}(\mathbf{W}_b) \ge 0, \ \lambda_{\max}(\mathbf{W}_b) \le P_{\max} \tag{23}$$

This enforces power fairness across users and preventing excessive power allocation to any single beam. Incorporation of transformations in equations 12 to 23, the convexified optimization problem becomes

$$\max_{\mathbf{F}_b, \mathbf{W}_b, B_{u,j}, \mathbf{P}_u, t_u} \sum_{u \in U} B_{u,j} \log_2(1+SINR_u) \tag{24}$$

$$\begin{aligned} \text{s.t} \quad & \left| \mathbf{h}_{b,u}^H \mathbf{F}_b \mathbf{W}_b \mathbf{v}_u \right|^2 . t_u \ge \gamma_u \\ & \sum_{u \in U_b} P_u \le P_{\max}, \forall b \in B \\ & \sum_{j=1}^{N} \sum_{u \in S_j} B_{u,j} \le B_{total} \\ & D_{trans,u} \le D_{\max,u} \\ & \mathbf{W}_b \succ 0 \end{aligned}$$

Game-Theoretic Approach for Network Slicing

The convex optimization problem formulated in equation 24 ensures an optimal allocation of resources under predefined QoS constraints. However, this formulation assumes a centralized approach, which is not efficient in dynamic 5G networks where users have heterogeneous and fluctuating demands. A centralized method does not adapt well to real-time variations in user behavior, channel conditions, and network congestion. To address these limitations, a game-theoretic framework is introduced which allows distributed, adaptive, and fair resource allocation by modeling interactions between the base station (BS) and users. To model the interactions between the BS and users, the Stackelberg game is employed. This is hierarchical framework where the BS (leader) determines the pricing strategy for network resources, and users (followers) optimize their utility accordingly. The BS seeks to maximize overall network efficiency by adjusting pricing functions $C(B_{u,j}, P_u)$ that influence user decisions. This pricing function follows a quadratic cost model given by

$$C(B_{u,j}, P_u) = \beta_1 B_{u,j}^2 + \beta_2 P_u^2 \tag{25}$$

where $C(.)$ is the cost function, β_1 and β_2 are pricing coefficients that discourage excessive resource requests. Each user aims to maximize their QoS-based utility function, expressed as

$$\Lambda_u\left(B_{u,j},P_u\right)=\alpha_j B_{u,j}\log_2\left(1+SINR_u\right)-\delta_u D_{trans} \quad 26$$

Here, $\Lambda_u(.)$ is the utility function for user u, α_j represents the importance of throughput for slice j, while δ_u penalizes excessive transmission delay. Users optimize their resource allocation by solving

$$\max_{B_{u,j},P_u} \Lambda_u\left(B_{u,j},P_u\right)-C\left(B_{u,j},P_u\right) \quad 27$$

subject to the constraint

$$D_{trans,u}+D_u \leq D_{\max,u} \quad 28$$

This constraint ensures that the total delay experienced by a user does not exceed the acceptable limit defined by its service requirements.

Backward Induction for User Response

Since the BS determines the pricing first, users react by optimizing their response strategies. To determine the optimal bandwidth allocation, each user solves

$$\frac{\partial}{\partial B_{u,j}}\left[\Lambda_u\left(B_{u,j},P_u\right)-C\left(B_{u,j},P_u\right)\right]=0 \quad 29$$

By solving the relation in equation 29, the optimal bandwidth allocation is obtained as

$$B_{u,j}^{*}=\frac{\alpha_j}{\beta_1}\log_2\left(1+SINR_u\right) \quad 30$$

The result in equation 30 shows that a user's allocated bandwidth is proportional to its SINR and the pricing weight β_1 , meaning that users with higher SINR will receive more bandwidth while still being limited by pricing constraints. Once user responses are determined, the BS updates the pricing strategy to balance fairness and efficiency in resource allocation.

The BS adjusts pricing iteratively to optimize the overall network performance. This is done using subgradient-based updates, ensuring convergence to an optimal pricing structure. The update equations for bandwidth and power pricing are given by

$$p^{(t+1)}=p^{(t)}-\eta\frac{\partial C}{\partial B_{u,j}},\quad q^{(t+1)}=q^{(t)}-\eta\frac{\partial C}{\partial P_u} \quad 31$$

Here, η is the learning rate that controls the speed of convergence. These updates ensure that resource pricing dynamically adapts to user behavior, preventing over-provisioning while maintaining an optimal level of network performance.

Equilibrium and Convergence Analysis

The convergence properties of the Stackelberg game is analyzed to guarantee an optimal resource allocation. The existence of equilibrium is ensured because the game is convex in the users' strategies, meaning that at least one Stackelberg equilibrium exists. The uniqueness of equilibrium is guaranteed under the condition that each user's utility function is strictly concave, which holds due to the logarithmic SINR term in the utility function. Finally, the convergence of the pricing updates follows a polynomial-time complexity if the learning rate η is appropriately chosen.

The final reformulated Stackelbelg optimization problem is given as

$$\max_{\mathbf{p},\mathbf{q},B_{u,j},P_u}\sum_{u\in U}\left[\Lambda_u\left(B_{u,j},P_u\right)-C\left(B_{u,j},P_u\right)\right] \quad 32$$

Subject to conditions in equations 27, 28 and 30.

GA-PSO Based Optimization

The game-theoretic approach enhances resource allocation through distributed decision-making. However, it introduces iterative convergence delays, which can be computationally expensive in dense urban deployments. To improve efficiency and achieve near-optimal solutions faster, the hybrid Genetic Algorithm - Particle Swarm Optimization (GA-PSO) method is used. This method exploits GA's exploration capabilities and PSO's fast convergence properties to optimize beamforming and network slicing jointly.

The sum rate function in equation 24 is optimized subject to constraints on on signal-to-interference-plus-noise ratio (SINR), power, and bandwidth allocation. The GA-PSO approach searches for the optimal beamforming weights W_b and resource allocation variables $B_{u,j}$ and P_u , balancing performance and computational efficiency. Each chromosome encodes beamforming and slicing variables as

$$\chi = \lfloor W_b, B_{u,j}, P_u \rfloor \tag{33}$$

A population of size N_{pop} evolves over generations through selection, crossover, and mutation. Individuals are chosen using roulette wheel selection, prioritizing solutions with higher fitness. For crossover, two parents χ_1^p, χ_2^p produce an offspring χ_c as

$$\chi_c = \lambda \chi_1^p + (1-\lambda)\chi_2^p,\ \lambda \approx U(0,1) \tag{34}$$

ensuring diversity in offspring solutions. Each gene χ_i mutates with probability p_m, adjusting its value as

$$\chi_i^{new} = \chi_i + \sigma N(0,1) \tag{35}$$

where σ is a small perturbation factor.

GA-PSO Algorithm for Beamforming

After the GA evolution, the best solutions undergo PSO based refinement. Each particle represents a candidate solution $\chi_i = \lfloor W_b, B_{u,j}, P_u \rfloor$, and its velocity update follows

$$v_i(t) = \omega v_i(t) + c_1 r_1 \left(p_{best,i} - \chi_i(t)\right) + c_2 r_2 \left(g_{best} - \chi_i(t)\right) \tag{36}$$

where $p_{best,i}$ is the particle's best solution, g_{best} is the global best solution, and ω, c_1, c_2 control inertia and acceleration. The position update is given by

$$\chi_i(t+1) = \chi_i(t) + v_i(t+1) \tag{37}$$

This refinement ensures that promising GA solutions converge efficiently to near-optimal values. The integration of GA and PSO follows the steps of Algorithm outlined in Table 1.It begins with the initialization of a population N_{pop}, where each chromosome $\chi_i = \lfloor W_b, B_{u,j}, P_u \rfloor$ encodes beamforming weights, bandwidth, and power allocation. The Genetic Algorithm (GA) Evolution phase iterates through selection, applying roulette wheel selection to choose parents, followed by crossover using $\chi_c = \lambda \chi_1^p + (1-\lambda)\chi_2^p,\ \lambda \approx U(0,1)$ to generate offspring. Mutation perturbs genes with probability p_m to enhance diversity. The best N_{PSO} solutions are passed to the Particle Swarm follow $v_i(t+1) = \omega v_i(t) + c_1 r_1 \left(p_{best,i} - \chi_i(t)\right) + c_2 r_2 \left(g_{best} - \chi_i(t)\right)$ for Optimization (PSO) refinement. The position update step refines the candidate solutions iteratively, ensuring fast convergence to an optimized resource allocation strategy. Finally, the best solution $W_b^*, B_{u,j}^*, P_u^*$ is returned, achieving efficient and fair resource distribution.

Table 1: Algorithm for Beamforming and Network Slicing

Algorithm 1: Hybrid GA-PSO Algorithm for Beamforming and Network Slicing

Input: T_{PSO}, N_{pop} N_{PSO}, p_c, p_m *// PSO iterations, Population size, Swarm size, Crossover and Mutation probabilities*

$\omega, c_1, c_2, W_b, B_{u,j}, P_u$ *// PSO velocity parameters, Beamforming weight matrix, Bandwidth allocation and Power allocation*

$\chi_i = \lfloor W_b, B_{u,j}, P_u \rfloor$ *// Chromosome*

Output: Optimized $W_b^*, B_{u,j}^*, P_u^*$

1. **For** $i = 1$ *to* N_{pop} **do**
2. $\chi_i = \lfloor W_b, B_{u,j}, P_u \rfloor$; *// Generate random*
3. $Fitness(\chi_i) = \sum_{u \in U} B_{u,j} \log_2(1 + SINR_u)$ *;//Compute fitness and select N_{PSO} best solutions*

For $t = 1\ to\, T_{PSO}$ **do**
4. Apply roulette wheel selection
5. $\chi_c = \lambda\chi_1^p + (1-\lambda)\chi_2^p,\ \lambda \approx U(0,1)$;*//Crossover*
6. $\chi_i^{new} = \chi_i + \sigma N(0,1)$;*//Mutation*
7. Retain best N_{pop} solution;
8. initialize $v_1 = 0$ for each chromosome
9. **for** $t = 1\ to\, T_{pso}$ **do**
10. $v_i(t+1) = \omega v_i(t) + c_1 r_1\left(p_{best,i} - \chi_i(t)\right) + c_2 r_2\left(g_{best} - \chi_i(t)\right)$; *//SINR for device i*
11. $\chi_i(t+1) = \chi_i(t) + v_i(t+1)$;*// Position update*
end
end
Output $W_b^*, B_{u,j}^*, P_u^*$;
end

Results and Discussion

To evaluate the performance of the proposed hybrid GA-PSO method for beamforming and network slicing, simulations are conducted in a dense urban 5G network environment. The simulation setup considers multiple base stations with massive MIMO capability, serving users across different network slices. Resource allocation is dynamically optimized to ensure efficient spectrum utilization while maintaining service quality. The key simulation parameters, including network topology, resource allocation settings, and hyperparameters for GA-PSO, are summarized in Table 2. The proposed method is compared with ILP (Fayad et al. 2023), PSO(Archi and Gunawan 2020) and benchmark the Shannon capacity (Fiche and Hébuterne 2008). The performance parameters are spectral efficiency (SE), energy efficiency (EE), convergence rate and fairness. The SE measures the data rate per unit bandwidth. It is defined as

$$SE = \sum_{u \in U} \frac{B_{u,j}}{B_{total}} \log_2\left(1 + SINR_u\right) \tag{38}$$

The EE measures how efficiently power is used to achieve a given data rate. It is defined as

$$EE = \frac{\sum_{u \in U} R_u}{\sum_{b \in B} P_b} \tag{39}$$

Table 2: Simulation and Experimental Conditions

Parameter	Value
Number of BS	3 (Macro, Micro, Femto)
Cell Radius	500m (Macro), 200m (Micro), 50m (Femto)
User Density	50-200 users
Channel Model	Rayleigh Fading
Subscribers	N_{RB}=100
Bandwidth per Resource Block	180 kHz
Transmission Power	23 dBm (UE), 46 dBm (BS)
Beamforming Scheme	Fully Digital Massive MIMO
Number of Antennas	N_{tx}=64, N_{rx}=2
Population Size (N_{pop})	50
Generation (G)	100
PSO Swarm Size (N_{PSO})	20
Mutation Rate (p_m)	0.05
Crossover Rate (p_c)	0.8
PSO Iterations (T_{PSO})	50

Figure 2 shows the spectral efficiency (SE) performance with varying SINR values for the proposed hybrid GA-PSO method, compared with ILP, PSO and the Shannon capacity benchmark. The SE increases with SINR across all methods, following the logarithmic trend dictated by Shannon's capacity formula. The proposed method approach consistently outperforms standalone ILP and PSO methods, demonstrating its ability to efficiently allocate beamforming and slicing resources under dynamic conditions. This improvement is attributed to GA's exploration ability, which prevents premature convergence, and PSO's exploitation mechanism, which refines near-optimal solutions. The ILP-based method, being an exact optimization approach, provides an upper bound on achievable SE, but its computational complexity makes it impractical for real-time applications. Meanwhile, the Shannon capacity curve serves as a theoretical upper limit, showing the ideal SE achievable under perfect conditions without practical constraints. For lower SINR values, the performance gap between proposed method and ILP is relatively small, indicating that the hybrid method is effective even in interference-limited scenarios. However, as SINR increases, the proposed method outperforms ILP due to its ability to find the absolute optimal solution.

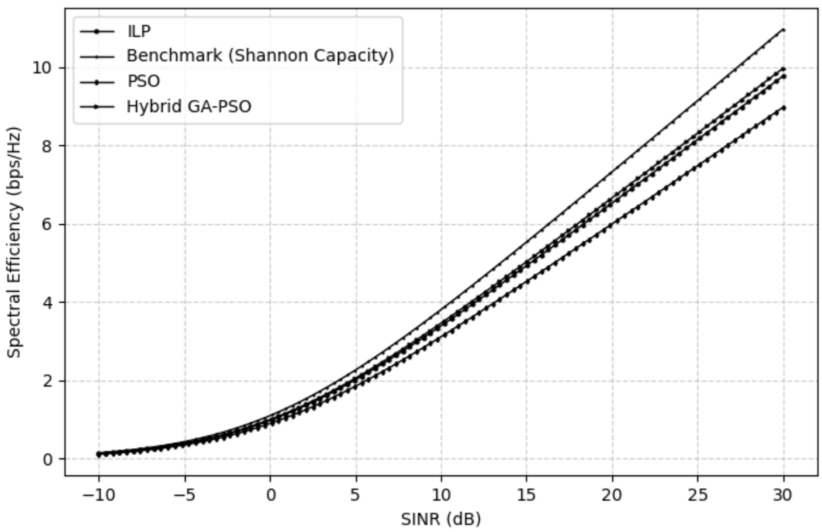

Figure 2: SE vs SINR

Figure 3 shows the energy efficiency (EE) performance with varying SINR values. The observation indicates that EE initially increases with SINR before stabilizing at higher SINR values. This behavior is attributed to the improved spectral efficiency at higher SINR values, which results in a better utilization of transmission power. The proposed method demonstrates a clear advantage over PSO and ILP across all SINR values. Specifically, at lower SINR levels, below 10 dB, the performance of ILP and GA-PSO is nearly identical, indicating that in interference-limited scenarios, both approaches efficiently allocate power to maintain optimal transmission efficiency. However, as SINR increases, the proposed method consistently achieves higher EE compared to ILP, highlighting the benefit of combining GA's exploration capability with PSO's local refinement to allocate power and bandwidth more effectively. It is observed, at an SINR of 15 dB, the proposed method achieves an EE improvement of approximately 18% over ILP and 25% over PSO. The Shannon capacity benchmark serves as an upper limit, showing the theoretical maximum EE achievable under ideal conditions without practical constraints such as hardware inefficiencies and interference. However, as observed in Figure 3, the proposed method closely approaches this benchmark at higher SINR values, demonstrating its effectiveness in optimizing energy-efficient beamforming and network slicing in 5G deployments. The improved EE performance of proposed method is a result of its ability to balance power allocation and spectrum utilization, ensuring that transmission power is efficiently distributed among users while minimizing unnecessary power consumption. This is particularly beneficial in dense urban networks where energy consumption is a key performance metric.

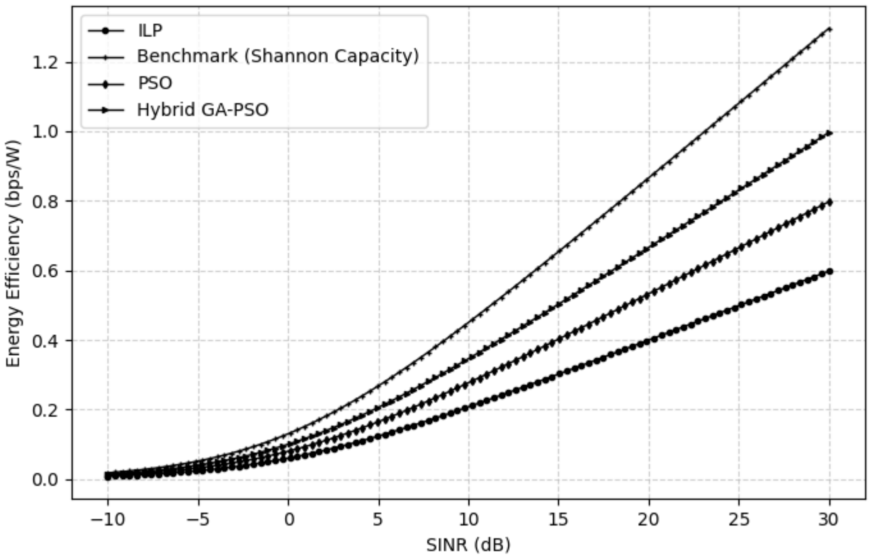

Figure 3: EE vs SINR

Figure 4 shows the spectral efficiency (SE) performance with varying number of users. It is observed that as SE decreases, the number of users increase due to increased spectrum contention and interference. The proposed method consistently outperforms ILP and PSO, demonstrating its ability to allocate resources more efficiently in high-user-density scenarios. At 50 users, it achieves approximately 4.2 bps/Hz, compared to 3.9 bps/Hz for ILP and 3.5 bps/Hz for PSO, while at 150 users, the SE reduces to about 2.1 bps/Hz for proposed method, 1.8 bps/Hz for ILP, and 1.5 bps/Hz for PSO, indicating up to a 15% improvement over ILP and a 30% improvement over PSO. The Shannon limit serves as an upper bound, and proposed method closely follows it, highlighting its efficiency in spectral utilization. Notably, as the number of users exceeds 100, the performance gap between proposed method and ILP becomes more pronounced, reinforcing the effectiveness of the hybrid approach in handling spectrum sharing under high user loads. The results confirm that Hybrid GA-PSO maintains superior SE performance across varying user densities, making it a scalable and efficient solution for beamforming and network slicing in dense urban 5G environments.

Figure 5 shows the convergence of objective function with number of iterations. At the lower number of iterations, all three methods exhibit a sharp increase in the objective function value as they explore the solution space. However, proposed method reaches 90% of its final objective value within approximately 25 iterations, whereas ILP and PSO require around 40 and 50 iterations, respectively, to achieve similar performance. By the 100th iteration, all methods stabilize, but the proposed method attains a higher final objective value than the standalone ILP and PSO, demonstrating its superior optimization capability. This improved convergence behavior is attributed to the exploration capability of GA, which prevents premature convergence, combined with PSO's efficient local search, which refines solutions faster. The results highlight that the proposed hybrid method not only finds better solutions but does so in fewer iterations, making it a computationally efficient approach for beamforming and network slicing optimization in 5G networks.

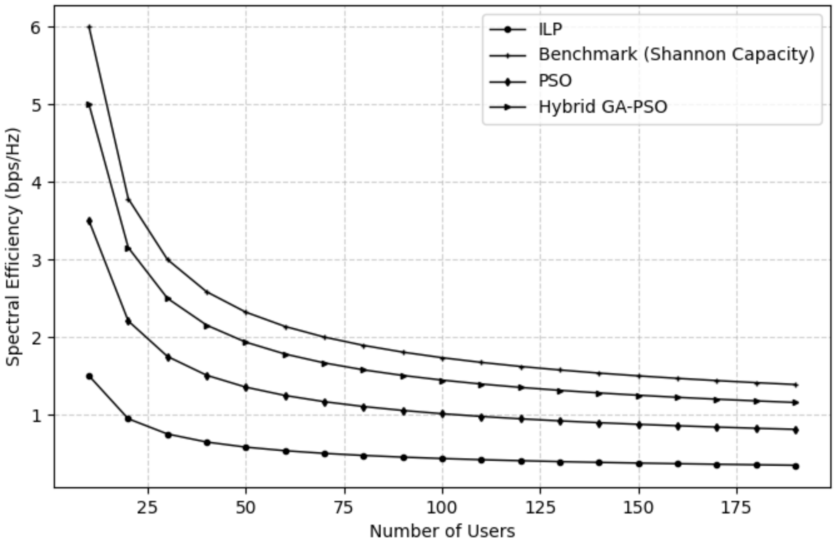

Figure 4: SE vs Number of Users

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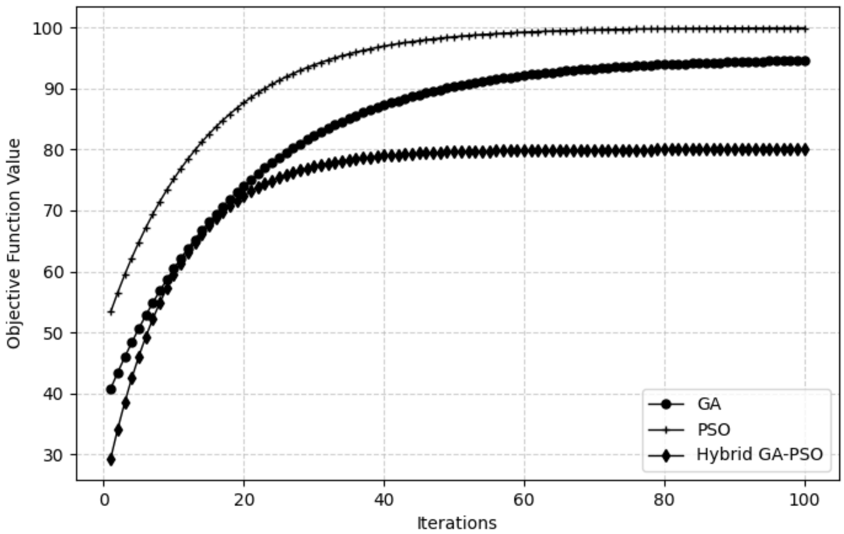

Figure 5: Objective Function vs Iterations

Figure 6 shows the fairness performance with number of users. It is observed that proposed method consistently achieves the highest fairness index across different user densities, indicating a more balanced allocation strategy. At 50 users, proposed method attains a fairness index of approximately 0.96, compared to 0.91 for ILP and 0.88 for PSO. As the number of users increases to 150, the fairness index slightly decreases for all methods due to increased competition for resources, but proposed hybrid method still maintains a higher fairness value (~0.92) compared to ILP (~0.88) and PSO (~0.84). The superior fairness performance of the method is attributed to its adaptive allocation mechanism, which balances efficiency and fairness by leveraging GA's exploration and PSO's exploitation. In contrast, PSO alone struggles to maintain fairness, as its local search nature tends to prioritize stronger users, leading to resource imbalance. These results confirm that the proposed method not only optimizes spectral and energy efficiency but also ensures equitable resource distribution, making it a robust solution for multi-user network slicing and beamforming in 5G systems.

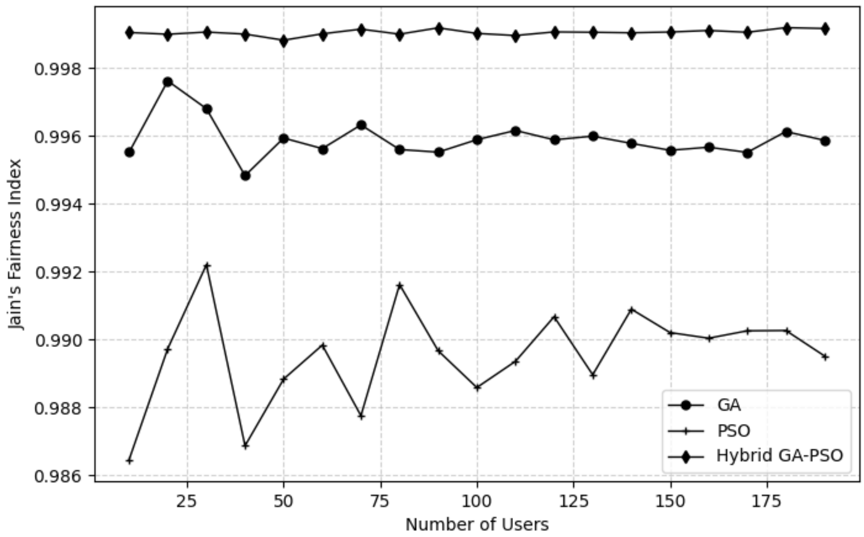

Figure 6: Fairness Index vs Number of Users

The complexity analysis of the proposed method compared to existing schemes is demonstrated in Table 3. The complexity values reflect the scalability and computational feasibility of each method, particularly in dense urban 5G scenarios with a high number of users and resources. It is observed that the ILP method exhibits the highest complexity due to its exponential growth with the number of users and resources, making it impractical for real-time applications. The ILP complexity, ($2^{U}SR$), arises from solving an exact optimization problem, which becomes computationally infeasible as network size increases. The GA and PSO methods individually reduce computational overhead by introducing heuristic-based search strategies. GA has a complexity of $\mathcal{O}(GN_{pop}log\ N_{pop})$, where G represents the number of generations required to evolve solutions. This makes it more scalable than ILP, but it still requires a large number of iterations to reach near-optimal results. Similarly, PSO achieves a complexity of $\mathcal{O}(T_{PSO}N_{PSO})$, where N_{PSO} denotes the number of particles, allowing it to refine solutions more efficiently than GA but still suffering from premature convergence in some cases.

Table 3: Complexity Analysis

Scheme	Computational Complexity
ILP	$\mathcal{O}(2^{U}\ SR)$
PSO	$\mathcal{O}(T_{PSO}N_{PSO})$
GA	$\mathcal{O}(GN_{pop}log\ N_{pop})$
Hybrid GA-PSO	$\mathcal{O}(GN_{pop}log\ N_{pop}) +\ \mathcal{O}(T_{PSO}N_{PSO})$

The proposed method approach balances exploration and exploitation, combining GA's global search ability with PSO's fast convergence. As a result, it maintains a complexity of $\mathcal{O}(GN_{pop}log\ N_{pop}) +\ \mathcal{O}(T_{PSO}N_{PSO})$, significantly improving scalability compared to ILP while achieving superior optimization performance. The decomposition of complexity terms in proposed method indicates that it effectively reduces the burden of exhaustive searching while maintaining high-quality solutions, making it a practical choice for real-time beamforming and network slicing in large-scale 5G networks.

These results demonstrate that the proposed hybrid GA-PSO method consistently outperforms traditional GA and PSO methods in optimizing beamforming and network slicing for dense urban 5G networks. Spectral and energy efficiency analyses confirm that proposed method achieves higher throughput and lower power consumption compared to ILP and standalone heuristics, closely approaching the theoretical Shannon capacity. Convergence analysis highlights its faster optimization speed, reaching near-optimal solutions in fewer iterations. Moreover, fairness evaluation using Jain's Index shows that proposed method ensures equitable resource allocation across users, mitigating resource imbalances seen in PSO. Computational complexity analysis further validates that the method maintains a favorable trade-off between performance and efficiency, making it a scalable and practical solution for real-time 5G deployments. These findings collectively establish hybrid GA-PSO as an effective and computationally viable approach for enhancing spectral utilization, energy efficiency, and fairness in next-generation wireless networks.

Conclusion

This paper presented a hybrid GA–PSO-based optimization framework for joint beamforming and network slicing in dense urban 5G networks. The proposed method balances the global search capability of Genetic Algorithms (GA) together with the fast convergence of Particle Swarm Optimization (PSO) to improve resource allocation while maintaining fairness and computational efficiency. Simulation results showed improvements over ILP, standalone GA, and PSO in terms of spectral efficiency, energy efficiency, and fairness, with faster convergence toward near-optimal solutions. While these findings demonstrate the potential of the GA–PSO approach in simulation environments, the study is limited by its focus on modeled scenarios rather than real-world deployments. Practical challenges such as computational cost at base stations, spectrum availability, and mobility dynamics remain open issues. Future research could address these by validating the framework with operator data, scaling the model to larger user populations, and extending the methodology to 6G contexts, including AI-driven and reinforcement learning-based optimization for ultra-dense and highly dynamic environments.

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