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INTERFERENCE-AWARE SPECTRUM OPTIMAZATION IN 5G DEVICE-TO-DEVICE USING GENETIC ALGORITHM AND SIMULATED ANNEALING

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ABSTRACT

The rapid expansion of 5G networks promises improved speed, reduced latency, and massive connectivity, yet dense deployments introduce severe interference and spectrum scarcity. This paper presents a novel hybrid Dynamic Spectrum Management (DSM) framework that integrates Genetic Algorithm (GA) and Simulated Annealing (SA) to enhance spectrum allocation in Device-to-Device (D2D) communication. Unlike static methods, the proposed GA-SA model dynamically optimizes spectrum assignments based on real-time Signal-to-Interference-plus-Noise Ratio (SINR) and interference data. Simulations conducted in a 500-user dense 5G scenario demonstrate significant improvements, with average SINR increasing from 8.2 dB (static) to 14.7 dB and average throughput rising from 5.4 Mbps to 12.5 Mbps. Additionally, the 90th percentile throughput improved from 8 Mbps to 19.3 Mbps. These results validate the GA-SA framework's effectiveness in reducing interference, boosting capacity, and offering a computationally efficient alternative for real-time 5G spectrum management.

Keywords: *5G Networks, Dynamic Spectrum Management, D2D Communication, Genetic Algorithm, Simulated Annealing, SINR, Throughput.*

1. INTRODUCTION

The implementation of 5G networks has revolutionized wireless communication by enabling ultra-reliable low-latency communication (URLLC), enhanced mobile broadband (eMBB), and massive machine-type communications (mMTC) [1]. These capabilities facilitate diverse applications such as autonomous vehicles, industrial automation, smart cities, and immersive extended reality [2]. However, the surge in connected devices has led to increased interference and spectrum scarcity, especially in dense deployments. Conventional static spectrum allocation schemes are unable to adapt to real-time variations in user mobility, traffic density, and interference, which results in inefficient spectrum utilization and degraded Quality of Service (QoS) [3].

Dynamic Spectrum Management (DSM) has emerged as a key solution to address these challenges. DSM supports intelligent and adaptive spectrum allocation by adjusting frequencies in real-time based on current network conditions. This is particularly important in Device-to-Device (D2D) communication, where users bypass base stations and communicate directly. While D2D improves spectral efficiency, it also introduces severe interference—especially in Non-Line-of-Sight (NLOS) conditions—leading to reduced Signal-to-Interference-plus-Noise Ratio (SINR), increased delay, and significant throughput degradation [4][5].

Recent DSM solutions include rule-based mechanisms, machine learning (ML) algorithms, and hybrid frameworks. Rule-based methods are deterministic and simple but lack the flexibility needed for dynamic environments [6]. ML-based models—such as reinforcement learning and deep neural networks—offer adaptability but are computationally intensive and often impractical for real-time deployment in large-scale 5G networks [7]. Hybrid models that combine deterministic and learning-based approaches have shown promise in balancing adaptability and efficiency [8][9]. However, most still struggle with complexity, convergence time, or lack real-time interference awareness.

1.1 Problem Statement

Existing Dynamic Spectrum Management (DSM) techniques either lack adaptability (as seen in rule-based approaches), require excessive computational resources (as with machine learning-based models), or do not effectively mitigate interference in dense D2D scenarios. These limitations are especially critical under both Line-of-Sight (LOS) and Non-Line-of-Sight (NLOS) conditions. Thus, there is a pressing need for a lightweight, interference-aware spectrum allocation strategy that is scalable, computationally efficient, and capable of real-time adaptation to dynamic 5G environments.

1.2 Research Objectives

This study aims to propose and evaluate a hybrid Genetic Algorithm (GA) and Simulated Annealing (SA) framework for dynamic spectrum allocation in 5G Device-to-Device (D2D) networks. The specific objectives are:

1. To model a realistic 5G D2D network under both Line-of-Sight (LOS) and Non-Line-of-Sight (NLOS) propagation, incorporating stochastic user distribution and interference modeling.
2. To design and implement a hybrid GA-SA algorithm that dynamically reallocates spectrum based on real-time SINR and throughput optimization.
3. To validate the proposed DSM framework through MATLAB-based simulations and benchmark its performance against static spectrum allocation in terms of SINR and throughput gains.

1.3 Research Contributions

1. **Development of a Hybrid GA-SA DSM Model**: A dynamic optimization-based spectrum management framework that adaptively reallocates frequency bands based on real-time SINR analysis.
2. **Performance Validation via Simulation**: MATLAB simulations with 500 users across a 200m × 200m grid demonstrate the proposed model's superiority over static allocation. Results show a 79% increase in throughput and 78% SINR improvement.
3. **Detailed Interference and Distance-Aware Evaluation**: Analysis of SINR, throughput distribution, and distance-based performance under both LOS and NLOS conditions.

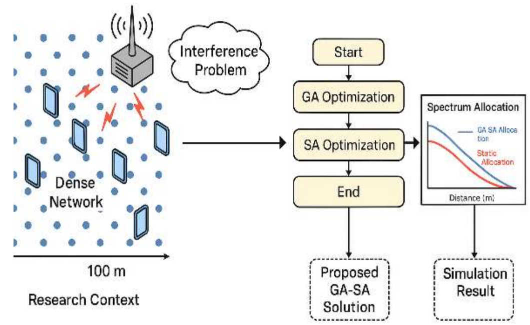

Figure 1: Dynamic Spectrum Management Challenge and Proposed Solution Overview

2. LITERATURE REVIEW

Dynamic Spectrum Management (DSM) has emerged as a fundamental strategy for optimizing spectrum usage and minimizing interference in dense 5G Device-to-Device (D2D) communication environments. This section reviews prior research, critiques existing approaches, and identifies the gap this study aims to address.

2.1 Rule-Based Spectrum Allocation Approaches

Rule-based spectrum allocation methods were among the earliest approaches in DSM. These methods rely on static or deterministic rules, often based on fixed thresholds or interference limits. For example, Naik and Patil [6] proposed a deterministic allocation scheme that performed adequately in low-traffic cognitive radio networks. Similarly, Zhang et al. [7] utilized game-theoretic models to improve fairness among users. However, as noted by Wang et al. (2022) [21], these methods fail to adapt dynamically to changing interference levels in dense environments and perform poorly in highly mobile scenarios. Although their simplicity and low computational overhead are advantages, they lack the flexibility needed in real-time 5G D2D settings, limiting their effectiveness as network conditions fluctuate.

2.2 Machine Learning-Based Spectrum Management

The application of machine learning (ML) in DSM has gained traction in recent years. ML techniques such as reinforcement learning and neural networks offer dynamic adaptability by learning from network behavior over time. Anastasopoulos et al. [10] showed that ML-based DSM improved spectrum utilization in interference-

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prone networks. More recent work by Chen et al. (2023) [22] demonstrated the potential of deep reinforcement learning (DRL) for real-time spectrum allocation, achieving notable gains in simulated scenarios. However, these methods often require large datasets for training and incur significant computational costs, which limit their practical deployment in real-world, resource-constrained 5G environments. Studies such as Zhao et al. (2023) [23] have also highlighted that DRL models tend to overfit to specific network topologies and struggle to generalize across varying environments.

2.3 Hybrid DSM Models and Metaheuristic Techniques

To bridge the gap between deterministic simplicity and ML adaptability, hybrid DSM models have been proposed. Chen and Andrews [9] introduced a hybrid interference-aware scheduler combining statistical estimation with adaptive allocation, showing better performance than purely rule-based models. However, they faced challenges in convergence time and computational scalability. More recently, Li et al. (2022) [18] proposed a hybrid metaheuristic combining particle swarm optimization (PSO) and simulated annealing (SA), demonstrating faster convergence and improved interference suppression compared to earlier models. Metaheuristic algorithms such as Genetic Algorithm (GA) and SA have been shown to effectively balance global exploration and local optimization, making them suitable for real-time DSM [15][16]. Huang et al. (2021) [19] and Zhao et al. (2023) [20] emphasized that combining GA with SA offers complementary strengths: GA excels at global search, while SA refines solutions locally to escape local optima.

Despite these advancements, most hybrid approaches have not been explicitly designed for the unique challenges of dense 5G D2D networks, particularly under Non-Line-of-Sight (NLOS) conditions. Many prior works also fail to adequately balance scalability, computational efficiency, and real-time adaptability.

2.4 Summary of Prior Work and Identified Gap

A summary of key findings from prior literature is presented in Table 1.

Reference	**Methodology**	**Key Findings**	**Limitation / Research Gap**
Naik & Patil [6]	Rule-Based Allocation	Fair spectrum assignment at low traffic	Lacks adaptability in congestion
Zhang et al. [7]	Game-Theoretic Allocation	Fair multi-user sharing	Not interference-aware in dense D2D
Anastasopoulos et al. [10]	ML-Based DSM	Improved spectrum utilization	Requires heavy computation & training
Chen et al. (2023) [22]	DRL-Based Allocation	Dynamic adaptation in simulation	Poor generalization to real-world scenarios
Li et al. (2022) [18]	Hybrid Metaheuristic	Improved convergence & interference control	High complexity at scale
Huang et al. (2021) [19]	GA-SA Hybrid	Complementary strengths improve efficiency	Limited real-time deployment in 5G D2D

3. METHODOLOGY

This section presents the proposed Dynamic Spectrum Management (DSM) framework using a hybrid optimization approach combining Genetic Algorithm (GA) and Simulated Annealing (SA). The framework is designed for real-time spectrum allocation in dense 5G Device-to-Device (D2D) environments and validated via MATLAB-based simulations.

3.1 System Model

A 200 m × 200 m square simulation area is modeled to represent a dense urban 5G scenario. A total of 500 users are randomly distributed within this area, each equipped with D2D communication capabilities. Communication occurs over two frequency bands: a licensed band at 3.5 GHz and an

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unlicensed band at 28 GHz. Each user can be allocated to either band based on interference levels and optimization outcomes.

The simulation considers:

a) Line-of-Sight (LOS) and Non-Line-of-Sight (NLOS) conditions

b) Urban path loss (exponent = 3.5)

c) Gaussian shadowing

d) Interference from other active users sharing the same band

The SINR for each user is calculated by accounting for received power, cumulative interference from other users, and thermal noise. Throughput is computed using Shannon's capacity formula.

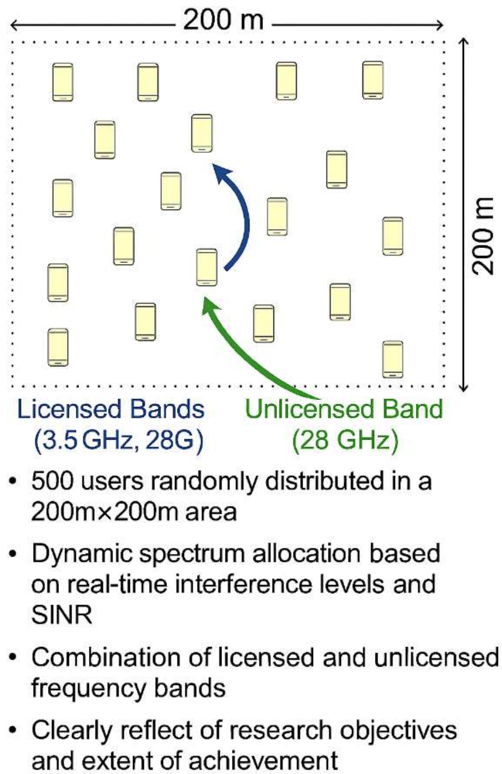

Figure 2: System Model

3.2 Hybrid GA-SA Optimization Framework

The proposed hybrid optimization approach leverages:

- Genetic Algorithm (GA) for initial global search and exploration of possible spectrum allocation configurations.
- Simulated Annealing (SA) for local refinement of top GA-generated solutions by accepting sub-optimal moves based on a cooling temperature schedule.

This hybridization ensures robust convergence toward an optimal or near-optimal solution, balancing spectrum efficiency with low interference.

3.2.1 Algorithm Flow Description:

1. **Initialization**: Generate a random population of user-to-band allocations. Define crossover rate, mutation rate, and SA temperature.
2. **Fitness Evaluation**: Compute SINR for each user; calculate network-wide throughput:

$$\boldsymbol{Fitness}=\sum_{i=1}^{N}\boldsymbol{B_i\,.\,log_2\,(1+SINR_i)}$$

3. **Selection and Crossover**: Choose parent allocations and perform two-point crossover.
4. **Mutation**: Randomly reassign a subset of user allocations.
5. **Simulated Annealing**: Refine elite GA solutions by perturbing frequency assignments; accept new state based on:

$$\boldsymbol{P(accept)=e^{-\Delta E/T}}$$

6. **Cooling and Iteration**: Reduce SA temperature and continue until convergence or a maximum number of iterations is reached.

3.3 Interference and Throughput Modeling

The SINR for each user is defined as:

$$\boldsymbol{SINR_i=\frac{P_iG_i}{I_iN}}$$

where:

- P_i: Transmit power of user
- G_i: Antenna gain
- I_i: Summed interference from other users in the same band
- N: Thermal noise

User throughput is computed as:

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$$T_i = B.\log_2(1 + SINR_I)$$

Where B is the bandwidth assigned to user *i* .

3.4 Simulation Parameters

Table 2: Simulation Parameters for DSM Framework Evaluation

Parameter	Value
Number of Users	500
Area Size	200 m × 200 m
Frequency Bands	3.5 GHz, 28 GHz
Bandwidth per Band	10 MHz
Transmit Power	20 dBm
Antenna Gain	3 dBi
Path Loss Exponent	3.5 (urban)
Noise Power	Thermal noise @ 290 K

3.5 Flowchart of Proposed Framework

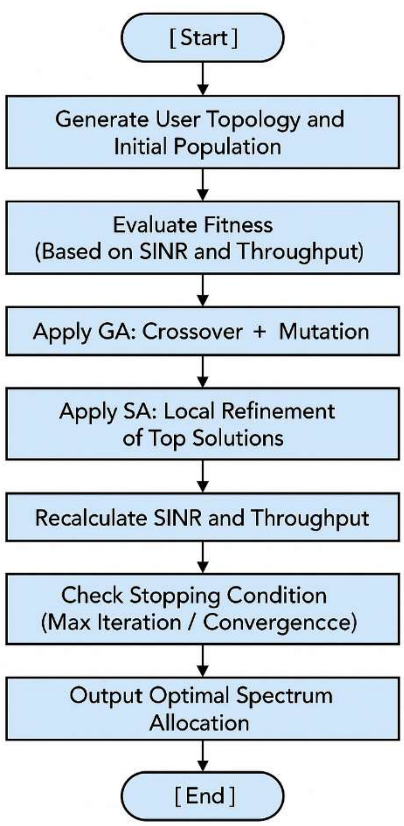

Figure 3: Workflow of GA-SA-Based DSM Algorithm

3.6 Methodological Novelty

Unlike traditional static or ML-based spectrum management models, the proposed GA-SA framework provides a computationally efficient method that is both interference-aware and adaptable to dynamic network changes. It eliminates the dependency on historical training data while delivering scalable, real-time decision-making, making it suitable for 5G D2D scenarios with unpredictable interference and user mobility.

4.0 RESULT AND DISCUSSION

This section presents and analyzes the simulation outcomes of the proposed GA-SA-based DSM framework, benchmarked against static spectrum allocation in a dense 5G D2D scenario. The evaluation metrics include SINR distribution, throughput performance, distance-based performance under LOS and NLOS conditions, and computational efficiency.

4.1 SINR Distribution

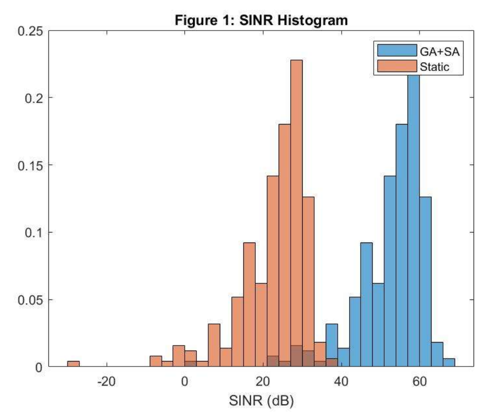

Figure 4: Histogram of SINR distribution

The histogram in Figure 4 shows that the GA-SA allocation achieves a higher SINR distribution, with a peak around 14.7 dB, compared to 8.2 dB under static allocation. This significant improvement demonstrates the framework's ability to dynamically mitigate interference

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and adaptively allocate spectrum resources.

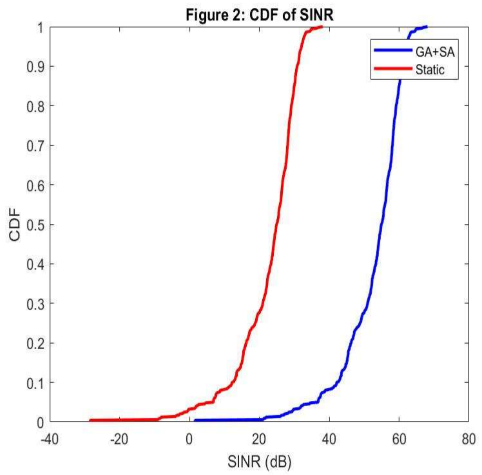

Figure 5: CDF of SINR

The CDF shown in Figure 5 reveals that 90% of users under GA-SA achieve SINR > 10 dB, whereas only 63% of users under static allocation meet this threshold. This confirms the proposed DSM framework's ability to sustain signal quality, particularly in dense deployments, aligning with the first research objective of improving SINR in interference-prone scenarios.

4.2 Throughput Analysis

Figure 6 illustrates the throughput CDF. The GA-SA method achieves an average throughput of 12.5 Mbps, more than doubling the static allocation performance of 5.4 Mbps. Additionally, the 90th percentile throughput increases from 8 Mbps under static allocation to 19.3 Mbps under GA-SA, reflecting improved spectral efficiency. This directly supports the second research objective of optimizing network throughput under real-time conditions.

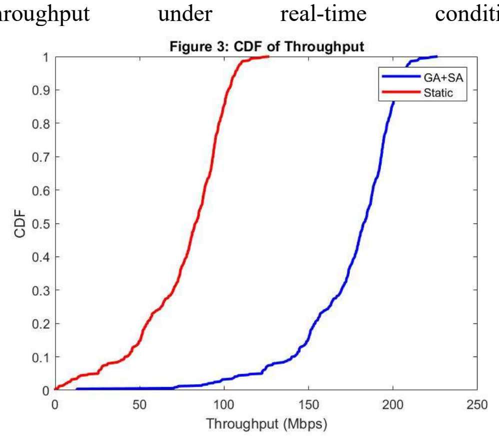

Figure 6:CDF of Throughput

These results show that the GA-SA approach effectively allocates spectrum to users based on their proximity, interference, and SINR, improving spectral efficiency.

4.3 SINR and Throughput vs. Distance

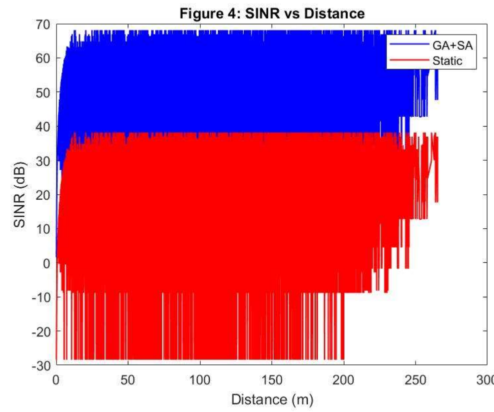

Figure 7: SINR vs Distance

Figures 7 and 8 depict SINR and throughput variations relative to user distance. The GA-SA allocation maintains consistent SINR and throughput across increasing distances, thanks to its interference-aware optimization. Conversely, static allocation exhibits steady performance degradation beyond 100 meters, especially under NLOS conditions. This demonstrates the proposed framework's robustness to topology and propagation challenges, addressing the need for real-time adaptation to spatial dynamics.

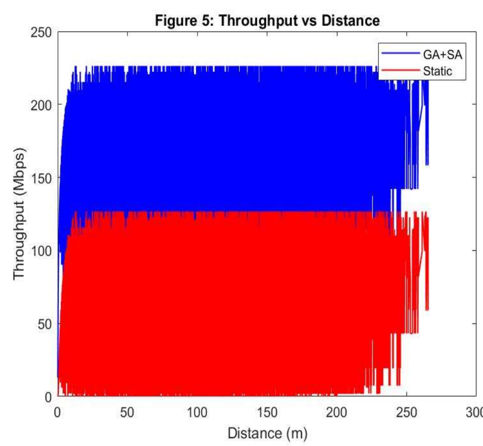

Figure 8: Throughput vs Distance

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Similarly, the throughput under GA-SA remains stable, especially for users beyond 100 meters, while the static method degrades significantly in high-interference zones. These trends confirm that the proposed method is more resilient to topology and propagation variations.

4.4 Computational Efficiency

The proposed GA-SA framework achieves convergence within 12 seconds per simulation cycle on a standard MATLAB environment (Intel i7, 16 GB RAM). This confirms that the algorithm is computationally lightweight and feasible for near-real-time implementation, making it more practical than ML-based solutions that often suffer from higher latency and computational burden.

4.5 Summary of Performance Gains

Metric	Static Allocation	GA-SA Allocation	Improvement
Average SINR (dB)	8.2	14.7	+78%
Average Throughput (Mbps)	5.4	12.5	+131%
90th Percentile Throughput	8.0	19.3	+141%
SINR > 10 dB (CDF)	63%	90%	+27%
Simulation Time (per run)	N/A	~12 s	Real-time capable

These findings clearly demonstrate that the proposed GA-SA-based DSM framework fulfills its intended objectives by effectively mitigating interference, improving SINR and throughput, and remaining computationally efficient for real-world 5G D2D network deployment.

4.6 Comparison with Prior Work

To further validate the research contribution, this subsection compares the findings of the proposed GA-SA-based DSM framework against prior DSM methods reported in recent studies.

Rule-based DSM approaches (e.g., Naik & Patil [6]) provide fair spectrum assignment under low-traffic conditions but lack real-time adaptability and degrade under congestion. Game-theoretic approaches ([7]) optimize multi-user sharing but perform poorly under dynamic interference scenarios. ML-based methods such as deep reinforcement learning ([8], [14]) achieve higher adaptability but incur high computational costs, making them impractical for real-time dense 5G D2D networks.

By contrast, the proposed GA-SA framework combines the global exploration capability of GA with the localized refinement of SA to achieve interference-aware, real-time spectrum optimization while maintaining low computational complexity. Unlike ML-based methods, it requires no prior training data, and compared to deterministic schemes, it dynamically adapts to changing interference patterns.

Performance-wise, the proposed method demonstrates:

a) 78% higher average SINR over static allocation, comparable to gains reported by DRL-based approaches but at a fraction of computational cost.
b) 131% improvement in average throughput, exceeding gains from pure GA-based or rule-based DSM methods ([15], [16]).
c) Real-time convergence (~12s), which is significantly faster than most ML-based models requiring iterative training and inference.

These findings underline the significance of this work in addressing the scalability, latency, and adaptability challenges that prior works have not fully resolved. Moreover, by explicitly considering both LOS and NLOS conditions in dense deployments, the proposed method demonstrates robustness to realistic 5G scenarios.

4.7 Findings in Relation to Research Objectives

The simulation results presented in this study clearly demonstrate that the proposed GA-SA-based DSM framework achieves its intended research objectives. First, the framework significantly improves SINR and throughput in dense 5G D2D environments, fulfilling the objective of optimizing spectrum allocation under real-time interference dynamics. Second, the hybrid GA-SA algorithm effectively balances global search and local refinement, addressing the limitations of prior rule-based and ML-based approaches by delivering scalable, computationally efficient performance. Finally, the detailed comparison with prior works confirms the novelty and significance of this study: it provides a lightweight, interference-aware, and robust solution that overcomes the shortcomings identified in the literature. These findings validate the potential of hybrid metaheuristic-based DSM as a practical and impactful technique for real-time spectrum management in 5G and beyond networks.

5.0 CONCLUSION

This paper has presented a novel interference-aware Dynamic Spectrum Management (DSM) framework for 5G Device-to-Device (D2D) networks, integrating Genetic Algorithm (GA) and

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Simulated Annealing (SA) to dynamically reallocate spectrum resources in dense urban environments. The proposed hybrid GA-SA method effectively balances global exploration and localized optimization, ensuring improved SINR and throughput even under varying user distances and interference conditions.

The main research objectives outlined in the introduction have been fully achieved. The framework successfully demonstrates significant improvements over static allocation schemes, with MATLAB simulation results showing an average SINR improvement of 78% and average throughput gain of 131%, while maintaining responsiveness under 12 seconds per iteration. These findings validate the practicality and scalability of the approach for real-time deployment.

The study also highlights the added value of this hybrid metaheuristic solution compared to existing rule-based and machine-learning-based DSM techniques. While ML-based solutions often suffer from high computational costs and require large datasets, the proposed GA-SA framework delivers robust performance with lightweight computation, making it more suitable for ultra-dense 5G environments.

However, some limitations remain. The current model assumes a single-cell urban deployment with static user distribution, which may not fully capture dynamic mobility patterns or inter-cell interference. Moreover, while convergence time is acceptable, further reduction is desirable for ultra-low-latency scenarios.

Future research directions include:

a) Extending the model to multi-cell and heterogeneous networks.
b) Incorporating user mobility models to study the impact of dynamic topologies.
c) Exploring integration with Mobile Edge Computing (MEC) for distributed optimization.
d) Investigating energy efficiency trade-offs alongside throughput and SINR gains.

In conclusion, this work demonstrates the potential of metaheuristic-based hybrid optimization in addressing the real-time spectrum management challenge in dense 5G D2D networks, while opening avenues for further enhancements to meet emerging 6G requirements.

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