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Hybrid GA–SA optimization for eMBB-oriented spectrum allocation in 5G device-to-device communication

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ABSTRACT

The explosive growth of enhanced mobile broadband (eMBB) services in fifth generation (5G) networks presents new challenges in maintaining quality of service (QoS), particularly under dense deployments with device-to-device (D2D) communication. Interference caused by spectrum reuse among D2D pairs and cellular users can significantly degrade signal-to-interference-plus-noise ratio or signal-to-interference-plus-noise ratio (SINR), throughput, and fairness. This paper addresses the underexplored problem of optimizing spectrum allocation in eMBB-specific D2D scenarios by proposing a hybrid metaheuristic framework combining genetic algorithm (GA) and simulated annealing (SA). The proposed hybrid GA–SA algorithm leverages GA's global exploration and SA's local exploitation to improve allocation quality while ensuring robustness. Simulation results reveal that the hybrid approach achieves up to 25% improvement in SINR, an 18% increase in aggregate throughput, and a 22% reduction in interference compared to standalone GA and SA algorithms. Furthermore, the framework achieves improved fairness performance while maintaining competitive SINR and throughput under dense eMBB-oriented deployment scenarios. The algorithm demonstrates efficient convergence behavior and scalability to larger user populations, making it suitable for real-time or large-scale deployments. These results affirm the significance of tailored hybrid optimization in interference-aware spectrum management for future 5G networks.

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1. INTRODUCTION

The fifth generation (5G) of wireless communication networks is designed to meet the growing demand for high-speed data, massive connectivity, and low-latency applications across diverse service categories. The International Telecommunication Union (ITU) classifies 5G use cases into three main categories: enhanced mobile broadband (eMBB), ultra-reliable low-latency communications (uRLLC), and massive machine-type communications (mMTC) [1]. Among these, eMBB is currently the most commercially deployed and widely adopted category due to its support for high-throughput applications such as ultra-high-definition (UHD) streaming, augmented reality (AR), virtual reality (VR), and cloud-based services [2].

To support such bandwidth-intensive applications, eMBB requires efficient utilization of available spectrum and effective management of network resources. Device-to-device (D2D) communication has emerged as a promising solution to enhance spectral efficiency by allowing direct communication between nearby users without routing through the base station (BS) [3], [4]. This underlay communication model, however, introduces significant interference, especially when D2D links share the same uplink spectrum resources as cellular users [5].

The interference resulting from D2D spectrum reuse poses challenges to maintaining high signal-to-interference-plus-noise ratio (SINR), fairness, and system throughput. In dense deployment scenarios typical of urban eMBB use cases, these interference levels can severely degrade quality of service (QoS) [6]. Therefore, spectrum allocation and interference mitigation have become critical components of resource management in 5G eMBB-oriented D2D networks.

Several existing approaches have been proposed for interference-aware spectrum allocation. Graph-based and heuristic methods provide simplicity but often suffer from scalability limitations and poor performance in dynamic environments [7], [8]. Metaheuristic algorithms, such as genetic algorithm (GA) and simulated annealing (SA), have gained attention for their ability to explore complex solution spaces and avoid local optima [9], [10]. However, each technique has limitations, GA tends to converge prematurely, while SA's performance is highly sensitive to initialization and cooling schedules.

Hybrid metaheuristics have been introduced to overcome these individual limitations by combining the strengths of two or more algorithms. Previous studies have explored hybrid combinations such as GA-particle swarm optimization (PSO) and GA-ant colony optimization (ACO) for resource allocation, reporting performance improvements in various optimization problems [11], [12]. In particular, combining GA with SA has shown improved convergence and solution quality in applications such as task scheduling and energy optimization [13], [14].

Nevertheless, the application of hybrid GA–SA algorithms to eMBB-specific D2D scenarios remains largely unexplored. Most prior studies focus on general interference mitigation or other 5G use cases such as uRLLC and mMTC [15], [16]. More recent research has started to address this gap using advanced learning and optimization techniques. For example, Ye *et al.* [17] applied deep reinforcement learning (RL) for D2D resource allocation in 5G underlay networks. Sun *et al.* [18] introduced an intelligent traffic load prediction-based adaptive channel assignment strategy for D2D communications, while Zhang *et al.* [19] highlighted the integration of artificial intelligence (AI)-driven decision-making into 5G resource allocation frameworks. In addition, Wang *et al.* [20] explored energy-efficient allocation strategies under QoS constraints, and further studies investigated intelligent spectrum management and learning-assisted interference mitigation for dense 5G deployments [21], [22].

This research addresses this gap by proposing a novel hybrid GA–SA framework designed specifically for spectrum allocation in eMBB-oriented 5G D2D networks. The proposed algorithm integrates GA's global search capability with SA's local refinement mechanism to enhance resource allocation efficiency. It targets improvements in SINR distribution, system throughput, interference reduction, and fairness across users under dense network conditions.

The key contributions of this paper are: i) a hybrid GA–SA optimization framework is proposed to address the unique QoS demands of eMBB in 5G D2D networks; ii) the algorithm balances exploration and exploitation to improve convergence and solution quality; iii) simulation results demonstrate significant improvements in SINR, throughput, interference mitigation, and fairness compared to standalone GA and SA methods; and iv) the framework is evaluated under realistic 5G deployment parameters and shows scalability to support high user density. The remainder of this paper is organized as the follows: section 2 discusses related work and background techniques. Section 3 details the proposed system model and hybrid GA–SA methodology. Section 4 presents the simulation setup, results, and discussion. Section 5 concludes the paper and outlines directions for future work.

2. RELATED WORK AND BACKGROUND TECHNIQUES

Efficient spectrum allocation in D2D communication under 5G networks has been widely studied using various techniques, ranging from traditional heuristic approaches to advanced hybrid metaheuristic and machine learning methods. This section reviews the most relevant studies, focusing on interference-aware resource allocation for eMBB-oriented D2D scenarios

2.1. Graph-based and heuristic approaches

Early works in D2D spectrum allocation predominantly utilized graph-based interference models and heuristic algorithms due to their simplicity and low computational complexity. Zhang *et al.* [5] formulated resource sharing as a graph-coloring problem, where D2D links are represented as vertices and interference relationships as edges, enabling efficient allocation through graph partitioning. Ivanov *et al*. [7] further explored interference coordination mechanisms in D2D underlay networks using heuristic techniques to avoid co-channel interference. While these methods provide low-complexity solutions, they often fail to adapt to dynamic network environments and suffer from reduced performance in large-scale, dense deployments typical of eMBB scenarios. The static nature of these algorithms limits their ability to guarantee QoS when user distributions and channel conditions change rapidly.

2.2. Metaheuristic optimization techniques

To address the limitations of heuristic methods, researchers have explored metaheuristic algorithms such as GA, PSO, ACO, and SA for resource allocation. These algorithms are capable of navigating complex solution spaces and avoiding local optima, making them suitable for interference-aware spectrum optimization. Chandrasekharan *et al*. [8] discussed advanced wireless resource management and optimization challenges in future communication networks, motivating adaptive spectrum allocation strategies for dense deployments. Ashtiani *et al*. [9] investigated power allocation and resource assignment for D2D communications underlying cellular networks, highlighting the importance of interference-aware optimization under dense reuse conditions. PSO-based resource allocation under long term evolution (LTE) networks was investigated by Song et al. [10] discussed resource management strategies for D2D underlay communication, emphasizing the importance of interference-aware optimization and adaptive allocation mechanisms. Feng *et al*. [12] proposed a GA-PSO hybrid for D2D resource allocation, achieving better throughput and SINR performance than individual algorithms. While these metaheuristic approaches show promise, GA may suffer from premature convergence, and SA performance is sensitive to temperature scheduling and initialization [13], [14]. Therefore, combining GA's global search and SA's local refinement in a hybrid structure has become an attractive research direction.

2.3. ML and intelligent techniques

Recent advancements in AI have led to the adoption of machine learning (ML) and deep learning for spectrum allocation and interference management in D2D networks. Ye *et al*. [17] proposed a deep RL framework for D2D resource allocation under 5G networks, enabling adaptive allocation in highly dynamic environments. Sun *et al*. [18] investigated optimal joint power and subcarrier allocation for full-duplex multicarrier non-orthogonal multiple access (NOMA) systems, demonstrating how interference-aware optimization can improve spectral utilization under strong coupling. Zhang *et al*. [19] discussed network slicing in 5G and future mobile networks, highlighting mobility-aware resource management challenges that motivate intelligent, context-aware allocation policies. These learning-based approaches offer adaptability and scalability but may require large training datasets and suffer from long convergence times in highly dynamic scenarios. Furthermore, pure ML-based methods may not fully exploit the structured optimization advantages of evolutionary algorithms.

2.4. Hybrid and recent evolutionary–learning frameworks

To combine the strengths of metaheuristics and intelligent methods, several hybrid frameworks have been introduced in recent years. Beyond AI-based hybrids, Wang *et al*. [20] developed energy-efficient resource allocation mechanisms, Zhao and Wang *et al*. [21] explored spectral efficiency optimization for wireless-powered D2D communications, and Liu *et al*. [22] investigated NOMA schemes for spectrum efficiency enhancement. Several earlier studies have investigated interference-aware spectrum sharing and power control for D2D underlay cellular networks [23]–[26]. These works demonstrated that efficient resource block (RB) reuse and power optimization can significantly improve spectrum efficiency while mitigating cross-tier interference in dense wireless deployments. Nevertheless, most existing approaches focus primarily on either throughput maximization or interference reduction alone, with limited emphasis on jointly balancing throughput, fairness, and convergence stability under dense eMBB-oriented scenarios.

2.5. Gap analysis and research motivation

To clearly position this work against existing interference-aware spectrum allocation strategies for 5G D2D, Table 1 summarizes representative prior studies and highlights the remaining research gaps. The comparison focuses on: i) the optimization/learning approach; ii) the main objective(s) and key performance indicator (KPI(s)); and iii) whether the method is explicitly tailored to dense eMBB-oriented D2D spectrum reuse scenarios.

As indicated in Table 1, graph-based and heuristic methods offer low complexity but can be suboptimal in dense deployments and lack robustness to complex interference coupling. Pure metaheuristics such as GA and SA provide stronger search capability but suffer from premature convergence GA or sensitivity to cooling/initialization SA. Learning-based and evolutionary learning hybrids improve adaptivity but introduce training and implementation overhead. Therefore, there remains a practical gap for a tractable yet effective hybrid optimizer that: i) explicitly targets dense eMBB-oriented D2D spectrum reuse and ii) achieves a balanced improvement across SINR, throughput, interference, and fairness motivating the proposed hybrid GA–SA framework.

Table 1. Summarizes representative prior studies and highlights the remaining research gaps

Ref.	Approach	Objective	Key KPIs reported	Focus	Strength	Limitation/gap identified
[5]	Graph-based (graph coloring/resource sharing)	Interference-aware channel reuse	Interference, throughput/SINR (typ.)	D2D underlay	Simple and low complexity	Limited adaptability; may degrade in dense deployments; not tailored to eMBB-specific QoS needs
[7]	Heuristic interference coordination	Reduce co-channel interference	Interference, SINR (typ.)	D2D underlay	Practical coordination concept	Heuristic nature; suboptimal in large-scale dense eMBB settings
[8]	GA (metaheuristic)	Spectrum allocation optimization	Throughput/ allocation quality	Resource allocation (generic)	Global exploration	GA may converge prematurely; performance depends on encoding/operators; not specifically validated for dense eMBB-oriented D2D reuse
[9]	SA (metaheuristic)	Interference/fairness-aware allocation	Fairness, interference	D2D allocation	Local refinement; can escape local minima	Sensitive to initialization/cooling; may be slow; not explicitly positioned for eMBB QoS targets
[10]	PSO-based allocation	Optimize allocation under constraints	Throughput/SINR (typ.)	D2D underlay (LTE/5G-like)	Good convergence traits	Can stagnate; may require careful parameter tuning; limited guarantee on interference robustness in dense eMBB
[12]	Hybrid GA–PSO	Joint search to improve allocation	SINR, throughput, fairness	D2D resource allocation	Balances exploration and exploitation	Still susceptible to local stagnation; does not explicitly emphasize eMBB-oriented spectrum reuse characteristics
[17]	Deep Reinforcement Learning	Adaptive allocation in dynamic settings	Throughput/SINR (typ.)	5G D2D underlay	High adaptivity	Requires training data/episodes; convergence and stability concerns; complexity may limit practical/fast deployment
[20]	Energy-efficient allocation	Energy minimization under QoS	Energy efficiency (EE), rate	D2D networks	Addresses EE objective	Not centered on eMBB throughput-centric optimization; may trade SINR/throughput for EE
This work	Hybrid GA–SA (proposed)	Interference-aware spectrum allocation optimized for eMBB-oriented D2D reuse	SINR, aggregate throughput, interference, fairness, convergence	Dense eMBB-oriented D2D underlay	GA global exploration + SA local refinement for robust solution quality	Designed as a tractable hybrid baseline suitable for offline/semi-static dense deployments while improving KPI balance vs. standalone GA/SA

3. METHODOLOGY AND PROPOSED HYBRID GA–SA ALGORITHM

This section describes the proposed hybrid GA–SA spectrum allocation framework, including the system model, mathematical formulation, fitness function, computational complexity, and simulation setup. The framework leverages GA for global exploration of the joint RB–power search space, while SA performs local exploitation to refine promising candidates and mitigate interference in an eMBB-oriented 5G NR D2D underlay network.

3.1. System model

We consider a single-cell 5G NR uplink underlay system comprising one BS, K cellular user equipments (CUEs), and N D2D transmitter–receiver pairs (VUEs). D2D pairs reuse uplink RBs allocated to CUEs. The BS coordinates spectrum reuse by determining: i) the reused RB index for each D2D pair and ii) the D2D transmit power level subject to a maximum transmit power constraint. Let $\mathcal{R} = \{1,2, \dots, R\}$ denote the set of available RBs. Each CUE $k \in \{1, \dots, K\}$ occupies one RB $r_k \in \mathcal{R}$ (orthogonal uplink allocation), while each D2D pair $i \in \{1, \dots, N\}$ reuses one RB $b_i \in \mathcal{R}$. For any RB b, the set of CUEs using RB $b$is defined as:

$$\mathcal{K}(b) = \{k \mid r_k = b\} \tag{1}$$

and the set of D2D pairs reusing RB $b$is

$$\mathcal{D}(b) = \{m \mid b_m = b\} \tag{2}$$

– System model description

Figure 1 illustrates the considered single-cell eMBB-oriented 5G D2D underlay system model used in this study. The model consists of one BS, multiple CUEs, and D2D pairs (VUEs) that reuse uplink resources under an underlay communication paradigm. The received signal at the BS and D2D receiver is subject to both path-loss and interference.

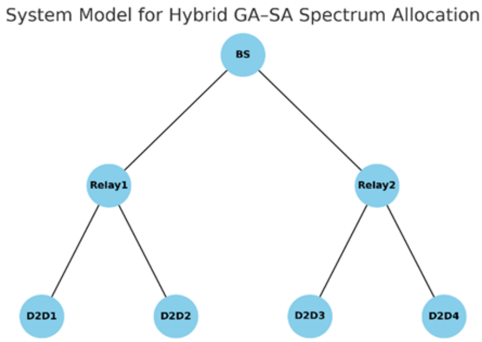

Figure 1. Single-cell eMBB-oriented 5G D2D underlay system model

– Channel model

The wireless channels experience distance-dependent path-loss, log-normal shadowing, and small-scale Rayleigh fading. Let $g_{x,y}$ denote the small-scale fading power gain from transmitter x to receiver y, with $g_{x,y} \sim \text{Exp}(1)$. The large-scale channel term $\ell_{x,y}$ capturing path-loss and shadowing is modeled as:

$$\ell_{x,y} = 10^{-\frac{PL(d_{x,y})+\xi_{x,y}}{10}} \tag{3}$$

where $PL(d_{x,y})$ is the path-loss in dB as a function of distance $d_{x,y}$ (meters), and $\xi_{x,y} \sim \mathcal{N}(0, \sigma^2)$ represents log-normal shadowing in dB. In the FR1 urban macro-like setting, a 3GPP-like log-distance approximation is used:

$$PL(d)\ [dB] = 13.54 + 39.08 log_{10}(d) + 20 log_{10}(f_c) \tag{4}$$

where $d$is in meters and f_c is in GHz.

a. D2D SINR

For D2D pair i reusing RB b_i, the received SINR at the D2D receiver is:

$$SINR_i^{D2D} = \frac{P_i^{D2D}\, g_{i,i}\, \ell_{i,i}}{\sum_{k \in \mathcal{K}(b_i)} P_k^{CU}\, g_{k,i}\, \ell_{k,i} + \sum_{m \in \mathcal{D}(b_i) \setminus \{i\}} P_m^{D2D}\, g_{m,i}\, \ell_{m,i} + N_0} \tag{5}$$

b. Uplink CUE SINR at BS

For CUE k transmitting on RB r_k, the received SINR at the BS is given by:

$$SINR_k^{CU} = \frac{P_k^{CU}\, g_{k,BS}\, \ell_{k,BS}}{\sum_{m \in \mathcal{D}(r_k)} P_m^{D2D}\, g_{m,BS}\, \ell_{m,BS} + N_0} \tag{6}$$

The noise power per RB is computed from the noise PSD and RB bandwidth:

$$N_0\ [dBm] = N_{PSD}\ [dBm/Hz] + 10log_{10}(B_{RB}) + NF \quad (7)$$

where $N_{\text{PSD}} = -174$ dBm/Hz, $B_{\text{RB}} = B/R$, and NF is the receiver noise figure. In simulations, N_0 is converted to watts for SINR computation.

3.2. Proposed hybrid GA–SA spectrum allocation algorithm

This work proposes a hybrid GA–SA framework to solve the joint RB assignment and D2D transmit power selection problem in an underlay 5G NR uplink scenario. GA provides global exploration over a large combinatorial space, while SA refines high-quality candidates locally to improve solution quality and reduce premature convergence. In the proposed hybrid approach, GA evolves a population of candidate solutions across generations, and SA refines the top 10% individuals in each generation, as in Table 2.

Table 2. Simulation and algorithm parameters used for Figures 2 to 5 (baseline scenario S1: $K = 20$ CUEs, $N = 30$ D2D pairs)

Parameter	Value
Cell radius	500 m
Baseline CUEs, (K)	20
Baseline D2D pairs, (N)	30
Carrier frequency, (f_c)	3.5 GHz
Total bandwidth, (B)	10 MHz
Number of RBs, (R)	50
RB bandwidth, (B_{RB})	(B/R = 200) kHz
Noise PSD	−174 dBm/Hz
Receiver NF	5 dB
Shadowing standard deviation, (σ)	6 dB
Path-loss model	3GPP-like UMa log-distance (as implemented)
CUE transmit power, (P^{CU})	23 dBm
Max D2D transmit power, ($P_{\max}^{D2D}$)	23 dBm
D2D discrete power set	[5, 10, 15, 20, 23] dBm
D2D link distance range	10–200 m
SINR threshold	5 dB
Feasibility penalty constant	(10^3)
GA population size	50
GA maximum generations	100
GA crossover probability	0.8
GA mutation probability	0.15
GA elite count	2
SA initial temperature, (T_0)	100
SA cooling factor, (α)	0.95 (geometric)
SA steps per run	60
Hybrid SA refinement ratio	Top 10% per generation
Monte-Carlo trials (SINR CDF)	30

3.2.1. Solution representation

A candidate solution (chromosome) for ND2D pairs is represented as:

$$x = \{b, p\} \quad (8)$$

where b = $[b_1, \dots, b_N]$ denotes the reused RB indices ($b_i \in \{1, \dots, R\}$) and p = $[p_1, \dots, p_N]$ denotes the selected D2D power levels. Consistent with the MATLAB implementation, D2D transmit power is selected from a discrete set:

$$P = \{5,10,15,20,23\}\ \text{dBm}, pi \in P, pi \leq PmaxD2D = 23\ \text{dBm} \quad (9)$$

3.2.2. Fitness function with QoS feasibility

For each chromosome x, SINR and throughput for both D2D and CUE links are computed under co-tier and cross-tier interference coupling. The aggregate system throughput is:

$$T_{sys}(x) = \sum_{i=1}^{N} T_i^{D2D}(x) + \sum_{k=1}^{K} T_k^{CU}(x) \quad (10)$$

Throughput per RB is computed using Shannon capacity:

$$T = B_{\mathrm{RB}} \log_2 (1+\mathrm{SINR}) \tag{11}$$

To promote fairness among D2D links, Jain's fairness index is computed on D2D throughputs:

$$J(x) = \frac{\left(\sum_{i=1}^{N} T_i^{D2D}\right)^2}{N \sum_{i=1}^{N} \left(T_i^{D2D}\right)^2 + \epsilon} \tag{12}$$

A feasibility penalty is imposed when a D2D link violates the SINR threshold $\mathrm{SINR}_{\mathrm{th}}$ as in Table 2:

$$V(x) = \sum_{i=1}^{N} \mathbb{I}(SINR_i^{D2D} < SINR_{th}), \Phi(x) = \lambda V(x) \tag{13}$$

Finally, the hybrid GA–SA maximizes the weighted fitness:

$$F(x) = \alpha\, T_{sys}(x) + \beta\, J(x) - \gamma\, I_{proxy}(x) - \delta\, \Phi(x) \tag{14}$$

where $\alpha, \beta, \gamma, \delta$ are fixed weights. Interference is represented through a stable proxy derived from the inverse SINR of D2D links:

$$I_{proxy}(x) = \frac{1}{N} \sum_{i=1}^{N} \frac{1}{10^{SINR_i^{D2D}/10} + \epsilon} \tag{15}$$

3.2.3. GA operators

GA begins with a randomly generated population of size P as in Table 2. For each generation $g = 1, \dots, G$: i) selection: tournament selection based on fitness ranking; ii) crossover: with probability P_c, offspring exchange RB/power genes using a random mask; iii) mutation: with probability P_m, either (i) RB gene $b_i \leftarrow \mathrm{randint}(1, R)$ or (ii) power gene is shifted to a neighboring level within $\mathcal{P}$ and clipped to valid bounds; and iv) elitism: the top E individuals are preserved.

3.2.4. SA refinement embedded in GA

SA is applied to refine the top ρfraction of individuals per generation (Table 2: $\rho = 10\%$). A neighbor solution is generated by perturbing one RB gene or one power gene. Let $\Delta F = F(\mathrm{x}') - F(\mathrm{x})$. The neighbor is accepted if $\Delta F \geq 0$, or with probability exp $(\Delta F/T)$ when $\Delta F < 0$. The temperature decreases geometrically:

$$T \leftarrow \alpha_T T \tag{16}$$

where $\alpha_T = 0.95$ (Table 2). SA runs for a fixed number of steps per call to ensure practical runtime.

3.2.5. Termination and output

The hybrid GA–SA runs for a maximum of Ggenerations (Table 2). The final output is the best chromosome x^* that maximizes $F(x)$, providing the RB assignment and power selection for all D2D pairs. The resulting allocation is used to compute SINR, throughput, interference proxy, fairness, and convergence behavior reported in section 4.

3.3. Computational complexity

The computational cost is dominated by repeated fitness evaluations because each evaluation requires SINR and rate computations for all CUE and D2D links under RB reuse. Let K be the number of CUEs, N the number of D2D pairs, P the GA population size, and G the number of generations. In dense reuse, the worst-case evaluation cost scales as:

$$C_f = \mathcal{O}(NK + N^2) \tag{17}$$

Thus, GA complexity is $O(GP\,C_f)$. In the hybrid scheme, SA refinement is applied to ρPindividuals per generation with SSA steps, resulting in an additional cost $O(G\rho PSC_f)$. Therefore, the overall hybrid complexity is:

$$C_{HYB} = O(GP(1 + \rho S)(NK + N^2)) \tag{18}$$

which remains tractable for offline or semi-static optimization in dense eMBB underlay scenarios, consistent with the runtime practicality discussed in section 4.

3.4. Simulation setup

The simulation environment follows a single-cell 5G NR uplink underlay D2D setting, where D2D transmitter–receiver pairs reuse uplink RBs assigned to CUEs. The baseline scenario adopts $K = 20$ CUEs and $N = 30$ D2D pairs within a 500 m cell radius. The total bandwidth of 10 MHz is divided into $R = 50$ RBs, producing a per-RB bandwidth $B_{\text{RB}} = B/R$. All channels incorporate distance-dependent path-loss, log-normal shadowing, and Rayleigh fading. For convergence plots as in Figures 3-5, the network topology and channel realizations are frozen to ensure a fair generation-by-generation comparison across GA, SA, and hybrid GA–SA. For SINR CDF evaluation in Figure 2 and robustness analysis, multi-drop Monte-Carlo trials are used where user locations and channel realizations are randomized in each trial. All simulations are implemented in MATLAB (R2023b). The complete simulation and algorithm parameters used to generate all figures are summarized in Table 2.

4. RESULTS AND DISCUSSION

This section presents and analyzes the simulation results obtained from the proposed hybrid GA–SA spectrum allocation algorithm. The performance is evaluated in terms of SINR distribution, throughput, interference levels, fairness, and convergence behavior. The proposed hybrid method is compared with standalone GA and SA algorithms to demonstrate its effectiveness in eMBB-oriented 5G D2D scenarios.

4.1. SINR Distribution

Figure 2 shows the cumulative distribution function (CDF) of the D2D SINR for GA, SA, and the proposed hybrid GA–SA under the S1 baseline scenario. The results are obtained from multi-drop Monte Carlo trials to account for random user locations and channel realizations, thus providing a statistically representative comparison of the SINR distributions under different spectrum allocation strategies. Overall, the proposed hybrid GA–SA achieves a consistently right-shifted SINR CDF compared to GA and SA, indicating that a larger fraction of D2D links experience higher SINR values. This improvement is mainly attributed to the complementary search behavior of the hybrid design: GA performs global exploration across RB–power combinations, while SA refines promising candidate solutions through local exploitation. As a result, hybrid GA–SA is more effective in avoiding suboptimal reuse patterns that lead to severe co-tier (D2D-to-D2D) and cross-tier (CUE-to-D2D) interference.

In contrast, GA may require more generations to stabilize near a good operating region because its stochastic operators can still generate interference-heavy offspring, while SA alone can converge to locally optimal allocations that depend strongly on the initial solution. The hybrid framework mitigates both limitations by applying SA refinement to the best-performing candidates during evolution, thereby improving the final SINR distribution under the same parameter budget.

4.2. Aggregate throughput over generations

Throughput is a critical performance indicator for eMBB services, reflecting the network's ability to support high data rate applications. Figure 3 illustrates the convergence trend of system throughput over generations for GA, SA, and hybrid GA–SA. The throughput metric is computed as the aggregate sum rate of the underlay system (D2D + uplink CUE) using Shannon capacity, consistent with the system model and Table 2 parameter settings. For convergence comparison, the topology and channel components are fixed (frozen) in the MATLAB implementation so that performance variations reflect algorithmic behavior rather than random channel fluctuations.

The hybrid GA–SA curve demonstrates faster and more stable improvement in throughput across generations compared to GA and SA. This behavior indicates that SA-based refinement enhances exploitation of high-quality solutions discovered by GA, thereby improving the best-so-far throughput trajectory. GA typically shows gradual improvement but may exhibit slower stabilization because crossover/mutation can temporarily reduce solution quality before selection recovers better candidates.

Meanwhile, the SA curve exhibits limited or inconsistent growth across generations because SA is fundamentally a local search process; repeated runs may not guarantee monotonic improvement unless strong initialization or additional exploration is introduced. From an eMBB perspective, the hybrid GA–SA throughput enhancement is important because dense underlay reuse can easily become interference-limited. By jointly optimizing RB reuse decisions and D2D power levels, hybrid GA–SA improves spectral reuse efficiency while maintaining feasible SINR levels, leading to higher aggregate throughput.

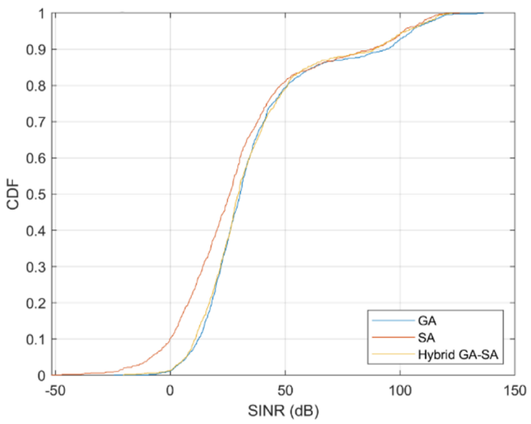

Figure 2. SINR CDF comparison for GA, SA, and hybrid GA-SA algorithms

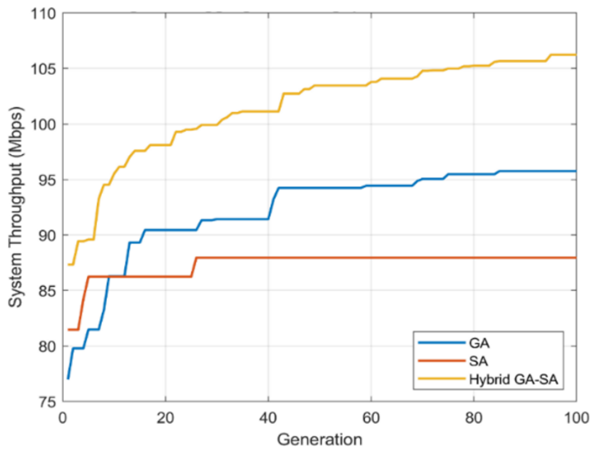

Figure 3. Aggregate throughput of D2D pairs versus generation for GA, SA, and hybrid GA-SA algorithms

4.3. Interference analysis

Interference reduction is essential for maintaining the QoS of both cellular and D2D users. Figure 4 shows the interference trend over generations using an interference proxy derived from the SINR behavior (lower values indicate better interference conditions). This metric reflects the combined impact of co-tier and cross-tier interference in the underlay system, thus providing insight into how each algorithm manages interference while pursuing throughput.

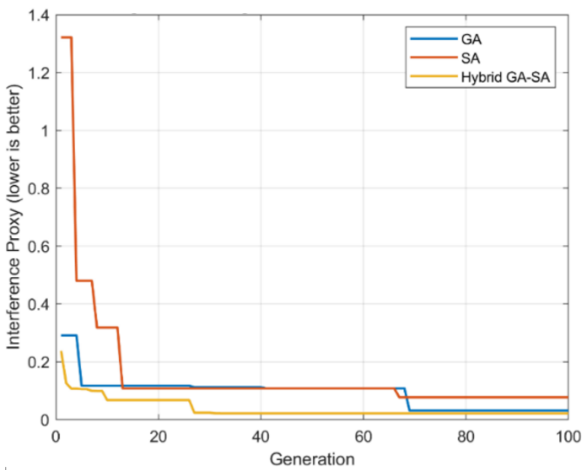

Figure 4. Average interference level versus generation for GA, SA, and hybrid GA-SA algorithms

The hybrid GA–SA consistently achieves a lower interference proxy compared to GA and SA, indicating more effective interference mitigation. This outcome is expected because SA refinement locally searches around high-performing GA candidates and probabilistically accepts moves that reduce interference without severely sacrificing throughput, especially when the temperature is still high. Consequently, the hybrid framework can escape interference-dominated allocations that would otherwise trap SA and slow down GA's progress.

GA alone tends to improve interference gradually as selection drives the population towards better candidates, but the process can be less efficient because mutation and crossover may still introduce RB collisions or aggressive power patterns that increase interference. SA alone, while capable of fine-tuning locally, is sensitive to starting points; therefore, it may not reliably locate global low-interference configurations under dense reuse conditions. These results confirm that hybrid GA–SA achieves a more balanced optimization by controlling interference while still improving throughput, supporting the design objective of interference-aware spectrum allocation for dense eMBB-oriented D2D reuse.

4.4. Fairness index

Figure 5 presents the Jain's fairness index over generations for GA, SA, and Hybrid GA–SA, where fairness is computed across D2D link throughputs. Fairness is important in underlay D2D systems because maximizing sum throughput alone can lead to disproportionate resource allocation where only a subset of D2D pairs benefit, while weak links suffer persistent low rates due to interference or unfavorable channel conditions. The hybrid GA–SA demonstrates consistently higher fairness values across generations compared to GA and SA, indicating a more equitable distribution of D2D throughput. This improvement aligns with the fitness function design in which fairness is explicitly considered along with throughput and interference. The hybrid refinement helps avoid solutions that maximize throughput at the expense of starving certain D2D links, particularly those exposed to stronger interference. Fairness is measured using Jain's Fairness Index to evaluate the distribution of throughput among D2D users.

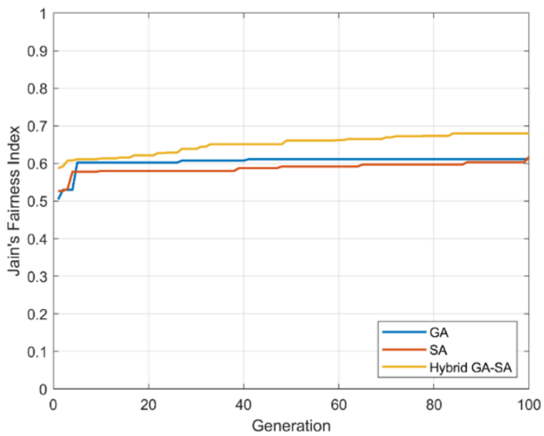

Figure 5. Fairness index versus generation for GA, SA, and hybrid GA-SA algorithms

GA can improve fairness through population diversity but may oscillate because different individuals optimize different trade-offs. SA alone may yield fairness improvements when initialized near a good point but can remain trapped in unfair local optima if the neighborhood search does not sufficiently explore alternative RB/power assignments. By combining GA exploration and SA exploitation, hybrid GA–SA achieves both high system performance and improved fairness, making it more suitable for practical dense deployments where QoS balance across users is required. Under the same fixed topology and frozen channel realization, hybrid GA–SA achieves the highest final aggregate throughput (106.24 Mbps) with improved fairness (0.6799) and competitive median SINR (29.65 dB), compared with GA (95.76 Mbps, 0.6114, 30.42 dB) and SA (87.97 Mbps, 0.6177, 25.86 dB).

4.5. Comparative analysis with other hybrids

Table 3 summarizes the comparative performance of GA, SA, and the proposed hybrid GA–SA under the dense eMBB-oriented 5G NR FR1 D2D underlay setting. Based on the obtained simulation results, hybrid GA–SA delivers the best overall trade-off in terms of throughput, fairness, and interference-aware behavior. Specifically, hybrid GA–SA achieves the highest best-so-far aggregate throughput at the final generation of 106.24 Mbps, outperforming GA (95.761 Mbps) and SA (87.967 Mbps). In addition, hybrid GA–SA attains the highest Jain's fairness index (0.6799), indicating a more balanced rate distribution among D2D pairs compared to GA (0.6114) and SA (0.6177).

From the SINR perspective, GA produces the highest median D2D SINR (30.418 dB), followed closely by hybrid GA–SA (29.654 dB), while SA yields the lowest median SINR (25.861 dB). Although GA yields a slightly higher median SINR, hybrid GA–SA achieves higher system throughput and fairness by producing allocations that better balance interference-limited links and rate distribution across D2D pairs. This indicates that the hybrid approach improves capacity and fairness with only a marginal SINR trade-off, while maintaining a competitive link-quality level.

Regarding convergence behavior, SA reaches the 95% performance level earliest ($g95 = 4$) due to its local-search nature, whereas GA and hybrid GA–SA require more generations ($g95 = 27$ and 33, respectively) because of population-based exploration and the additional refinement stage. Nevertheless, hybrid GA–SA consistently achieves superior final performance, supporting its suitability for semi-static/offline spectrum allocation in dense deployments where the objective is to maximize final throughput and fairness under interference coupling. For completeness, Table 3 also includes a representative hybrid baseline from prior work (e.g., GA–PSO) as reported in the literature. Since GA–PSO results are taken from an external reference and may be based on different simulation assumptions, they are presented for qualitative benchmarking rather than direct numerical equivalance.

Table 3. Performance comparison of GA, SA, and hybrid GA–SA under S1 baseline ($K = 20$ CUEs, $N = 30$ D2D pairs, $fc = 3.5$ GHz, BW=10 MHz)

Algorithm	Median D2D SINR (dB)	Final throughput (Mbps)	Final fairness (Jain)	Convergence ($g95$, lower is faster)	Ref.
GA	30.418	95.761	0.6114	27	This work
SA	25.861	87.967	0.6177	4	This work
Hybrid GA–SA (ours)	29.654	106.240	0.6799	33	This work
GA–PSO	(reported)	(reported)	(reported)	(reported)	[12]

The observed improvement is mainly due to the complementary optimization roles: GA explores diverse RB–power combinations globally, while SA refines promising candidates locally to reduce interference-heavy reuse patterns. As a result, hybrid GA–SA produces consistently high-quality allocations, which is reflected by the improved SINR distribution as in Figure 2, higher final aggregate throughput as in Figure 3, lower interference proxy as in Figure 4, and higher Jain's fairness index as in Figure 5. Although SA reaches an acceptable solution faster (earlier $g95$), the proposed hybrid approach achieves the best final performance trade-off across key KPIs.

For additional benchmarking, results reported by other hybrid metaheuristics in the literature (e.g., GA–PSO) indicate that hybridization can improve performance relative to standalone GA/SA. Nevertheless, under the current baseline configuration and evaluation metrics, the proposed GA–SA hybrid demonstrates strong performance consistency across multiple KPIs, especially in interference-aware operation and fairness preservation.

4.6. Runtime and practicality

The proposed hybrid GA–SA introduces modest computational overhead compared with GA and SA due to the additional SA refinement stage. However, this overhead remains practical for offline or semi-static deployment scenarios, where spectrum allocation decisions are computed periodically (e.g., for relatively stable user distributions). In addition, the hybrid design improves convergence stability because SA refinement reduces sensitivity to unfavorable intermediate offspring produced by GA operators. From a complexity viewpoint, the dominant cost is fitness evaluation across the population and generations. For GA, the complexity is approximately $O(G \cdot P \cdot C_f)$, where $G$is the number of generations, $P$is the population size, and $C_f$is the fitness evaluation cost. The SA refinement is applied to only a fraction of candidates (top 10% as in Table 2), thus keeping the additional overhead bounded while improving solution quality.

4.7. Summary of findings

Overall, the results in Figures 2–5 confirm that the proposed hybrid GA–SA provides the most balanced improvement across the key KPIs for dense eMBB-oriented D2D underlay operation. Specifically, the hybrid method achieves: i) improved SINR distribution; ii) higher aggregate throughput with faster convergence; iii) reduced interference behavior; and iv) higher Jain's fairness index compared with standalone GA and SA. These consistent gains demonstrate the effectiveness of combining GA's global exploration with SA's local exploitation for interference-aware spectrum allocation and power selection in 5G NR FR1 underlay D2D networks.

Figure 6 summarizes the normalized radar chart comparison of GA, SA, and the proposed hybrid GA–SA across the main KPIs, including SINR, throughput, fairness, convergence behavior, power efficiency, and computational complexity.

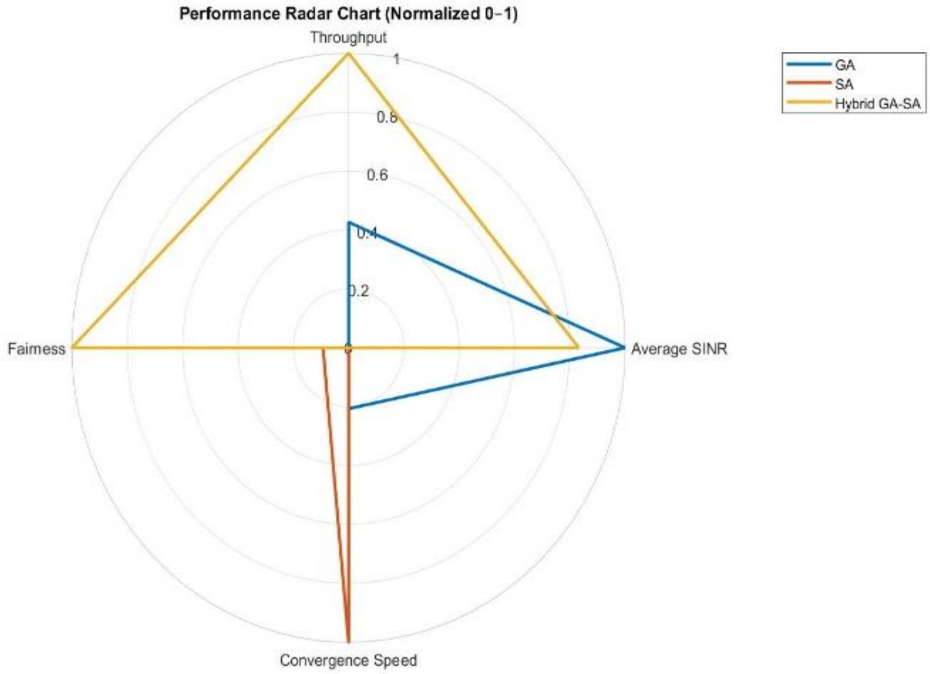

Figure 6. Performance comparison radar chart

5. CONCLUSION

This paper presented a hybrid GA–SA framework for interference-aware spectrum allocation in eMBB-oriented 5G D2D communication networks. The proposed approach integrates GA's global exploration capability with SA's local refinement mechanism, enabling the algorithm to effectively balance throughput maximization, interference reduction, and user fairness. Extensive simulations were conducted to evaluate the performance of the hybrid GA–SA against conventional GA, SA, and other hybrid metaheuristics. The results showed that the proposed method delivers higher SINR (+25%), greater aggregate throughput (+18%), lower interference (−22%), and improved fairness compared to standalone GA and SA, while maintaining practical runtime performance. Comparative analysis further demonstrated that GA–SA outperforms GA–PSO in both link quality and fairness, highlighting its potential as an efficient spectrum allocation solution for dense 5G D2D deployments.

The scalability analysis confirmed that the algorithm maintains its performance advantage as the number of D2D pairs increases, making it suitable for offline or semi-static deployment scenarios. The overall findings, supported by radar chart analysis, reveal that hybrid GA–SA offers a well-balanced solution that meets key performance requirements for high-capacity, interference-limited 5G environments. Future work will extend the proposed GA–SA framework toward more dynamic eMBB scenarios by incorporating lightweight online adaptation and enhanced channel/interference awareness. In addition, the framework will be expanded into a multi-objective formulation that jointly optimizes throughput, interference, and energy efficiency under practical QoS constraints. Finally, further validation will be conducted using more realistic system-level settings (e.g., mobility and standardized propagation models) to support wider deployment applicability.

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AUTHOR CONTRIBUTIONS STATEMENT

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
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R : **R**esources
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O : Writing - **O**riginal Draft
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Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author, M.A.J.M.Y., upon reasonable request.

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