Channel Allocation Optimization in Heterogeneous 6G Networks Using Genetic Algorithms

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**Abstract.** The deployment of sixth-generation (6G) networks introduces an unprecedented level of complexity due to the integration of diverse radio access technologies, dense heterogeneous infrastructures, and stringent Quality of Service (QoS) requirements. One of the key challenges in this environment is efficient and adaptive channel allocation that minimizes interference and maximizes spectral efficiency. This paper proposes a Genetic Algorithm (GA)-based optimization approach for dynamic channel allocation in heterogeneous 6G networks. The GA leverages population-based search, crossover, and mutation operators to explore the solution space efficiently and converge toward an interference-minimized allocation scheme. The system model considers user distribution, multi-tier network topology, and shared spectrum constraints. Simulation results demonstrate that the proposed method significantly outperforms traditional greedy and random allocation strategies in terms of interference reduction, throughput improvement, and convergence time. The findings validate the applicability of bio-inspired algorithms for resource allocation in next-generation wireless systems.

**Keywords:** Channel allocation, Genetic algorithm, 6G networks, Heterogeneous networks, Interference mitigation, Spectrum optimization, Metaheuristic optimization, Wireless resource management

# INTRODUCTION

The evolution of the sixth-generation (6G) wireless network is expected to change the communication world radically through proposal of unmatched performance of terabit-per-second transmission, sub-milliseconds latency, ultra- reliable low latency communication (URLLC), and massive connectivity of smart devices. Since 6G systems strive to accommodate various radio access technologies (RATs), such as millimeter-wave (mmWave), terahertz (THz), and non-terrestrial networks (NTNs), the management of radio resources development is highly dynamic and more complicated.

In this fast-developing environment, the heterogeneous network topologies (HetNets) will be of focus in expanding the coverage and capacity. Such HetNets are combined macro, micro, pico and femto cells which co-exist but occupy the same geographical area and the sharing of the spectrum and the infrastructure. As much as this design provides better user experience and throughput of the system, it aggravates co-channel interference and resource contention particularly in a dense deployment.

Radio resource management (RRM) consists essentially of channel allocation, the algorithm which allocates frequency or time slots to users. Supreme channel allocation within HetNets should be able to appoint fair access, great lessening of interferences, and supporting Quality of Service (QoS) needs of versatile and varying traffic weights. Conventional allocation algorithms, like fixed allocation or greedy heuristics, are usually not sufficient, since they do not scale, or adapt on-demand to changes in the network.

Due to the popularization of AI, as well as optimization in telecommunication, metaheuristic algorithms have become notable, including Genetic Algorithms (GAs), which excel in their flexibility and capability of a global search. GAs emulate the natural evolution using such mechanisms as selection, crossover, and mutation to sample the good solutions in high-dimensional spaces. Their intrinsic parallelism and resilience feature allows them to be apt at addresses dynamic channel allocation problems even in 6G networks.

Past works implemented GAs to 4G/5G networks mostly with respect to load balancing or power control. Nonetheless, there is little work done on the use of GAs to channel allocation solutions specifically about 6G HetNets that require more flexible and decentralized techniques. Also, there is required reconsideration of the traditional allocation models due to the advent of new radio interfaces and spectrum bands.

To the best knowledge of the authors, the scheme of a new GA-based channel allocation with a focus on heterogeneous 6G settings is proposed in this paper. Channel assignments are encoded as chromosomes and populations are evolved toward minimal interference solutions in iterative processes. Interference all over the system, fairness of the users and reuse of the spectrum is well tuned into the fitness function. The adaptive crossover and mutation rates are also used to further increase performance.

The model is confirmed by a large scale simulation of a synthetic 6G network topology with different user densities and diverse interference models. The efficiency of algorithm in terms of convergence rate, interference level, and throughput are performance measures used to check how effective it is when compared with baseline greedy and random methods.

The findings indicate that the GA incorporation of allocation seriously outwits the traditional techniques in terms of interference mitigation as well as the network bandwidth. The suggested algorithm offers an improved convergence and scalability rate and can be used in practical implementations in the upcoming 6G systems.

The rest of the paper is organized as follows: Section II discusses related work; Section III presents the system model; Section IV explains the proposed genetic algorithm; Section V details the simulation results and analysis; and Section VI concludes the paper with future research directions.

# RELATED WORK

Channel allocation and routing in heterogeneous wireless networks, particularly in Vehicular Ad Hoc Networks (VANETs) and energy-constrained sensor networks, have been widely studied in recent literature. Ather et al. [1] addressed the challenges of routing in heterogeneous vehicular environments and proposed a protocol tailored for improved coverage. Earlier, Tahira et al. [2] focused on the modeling and performance evaluation of VANETs with mixed node architectures, emphasizing the importance of simulation-driven optimization. Ather and Shukla [3] presented a comparative study of routing protocols using simulation-based analysis, reinforcing the impact of routing strategies on overall performance. Such insight was supplemented with Gupta et al. [4] comparing different routing algorithms in VANETs to set a benchmark of a performance metric.

In more recent investigations, researchers have shifted to smart people focused research on machine learning and intelligent network management. The study of Ignatyev et al. [5] on how satellite imagery can be used to classify urban roads with the help of neural networks proves the topicality of studies in the field of deep learning in terms of wireless communication planning and infrastructure-aware optimization. Ather et al. [6] discussed a cluster-head approach to energy-mediated routing mechanism built on convolutional neural network (CNN) in wireless sensor networks. This multi-objective optimization that they managed to attain is very pertinent to 6G applications that require energy efficiency and channel reuse to be dynamically balanced.

Regarding real-time, adaptability, and performance trade-offs, Kim et al. [7] conducted an experiment on the impact of routing protocols on the performance of VANET in several ways, as different protocols suitably vary depending on network loads. Similarly, Ather et al. [8] introduced an efficient route maintenance algorithm in VANETs which reacts dynamically to the topology changes. An extended and detailed survey by Ather and Saxena [9] then summarized the state of challenges up to date and advocated more adaptive and intelligent routing frameworks.

In the context of secure cloud-based communication, Bhardwaj et al. [10] explored scalable, privacy-preserving group data sharing schemes — relevant to distributed architectures in 6G where data privacy and multi-user access control remain critical. This aligns with emerging 6G research where security and performance must coexist. Additionally, Shukla and Ather [3] investigated simulation-based comparisons of protocols, revealing that even subtle routing design choices significantly affect link stability and packet delivery ratios.

Collectively, these works emphasize the growing convergence of intelligent algorithms, optimization strategies, and multi-layered wireless architectures. The present study builds upon these contributions by focusing specifically on channel allocation in heterogeneous 6G networks, employing a Genetic Algorithm (GA)-based approach for dynamic, scalable, and interference-aware optimization. Unlike previous works that either address routing or static allocation independently, our framework integrates topology-aware channel assignment with evolutionary learning, setting the stage for future extensions with hybrid AI models and real-time deployment scenarios.

# SYSTEM MODEL

Heterogeneous sixth-generation (6G) wireless communication network This paper examines a multi-layered sixth- generation (6G) wireless communication network with a layered infrastructure, such as macrocells, microcells, picocell, and femtocell. These types of cell were present within the same geographical locality and each offers different coverage and capacity. The macrocells give wide-area coverage with smaller cells like micro, pico, and femto doing a better job of providing local coverage in areas of high populations or indoors. The net is used by various and mobile users, who have a different Quality of Services (QoS) requirement. Its most important goal entails devising a channel assigning procedure that can adapt in real-time to the network situations and to generate minimal interference as well as the highest spectral efficiency.

## Network Topology and Assumptions

Let *B* = {*b*1*, b*2*, ..., bN*} consist of the set *N* of the base stations (BSs) installed in the four tier network architecture. Let *U* = {*u*1*, u*2*, ..., uM*} denote the set of *M* mobile user devices distributed throughout the area. Each base station operates over a shared set of channels *C* = {*c*1*, c*2*, ..., cK*}, where *K* is the total number of orthogonal frequency channels available in the system. The channels are reused across cells to increase spectral efficiency, subject to co-channel interference constraints.

Every user *u j* is associated with its nearest base station *bi* based on the strongest Received Signal Strength (RSS). To reduce the possibility of interference, a reuse distance constraint *d*reuse is applied. If two users are within this distance and are connected to different BSs, they must not be allocated the same channel unless interference is mitigated through advanced signal processing or spatial isolation techniques.

## Channel Conflict and Interference Modeling

To mathematically model interference, we define an interference matrix *I* of size *M* × *M*, where each entry indicates whether user *u j* interferes with user *uk* when both use the same frequency channel. This is formally represented as:

(1)

Let Φ : *U* → *C* represent a channel allocation function that maps each user to a channel. The total interference experienced across the network due to co-channel assignments is calculated as:

Interference = (2)

Here, *δ* is the Kronecker delta function, which returns 1 when both users are assigned the same channel and 0 otherwise.

The effective Signal-to-Interference-plus-Noise Ratio (SINR) for each user *u j* is modeled as:

(3)

where *Pj* is the transmit power of the serving BS, *Gj j* is the channel gain between BS *b j* and user *u j*, and *N*0 represents the background noise power. The denominator includes the cumulative interference from all users *uk* sharing the same channel and within interference range.

The optimization goal is to determine an allocation function Φ∗ that both maximizes the network utility and minimizes interference. This dual objective is captured in the following cost function:

(4)

The first term promotes higher SINR values, which lead to better link quality and data rates, while the second term penalizes channel reuse that leads to interference. The parameter *λ* is a penalty coefficient that controls the trade-off between performance and interference suppression.

## Mobility and Handoff Model

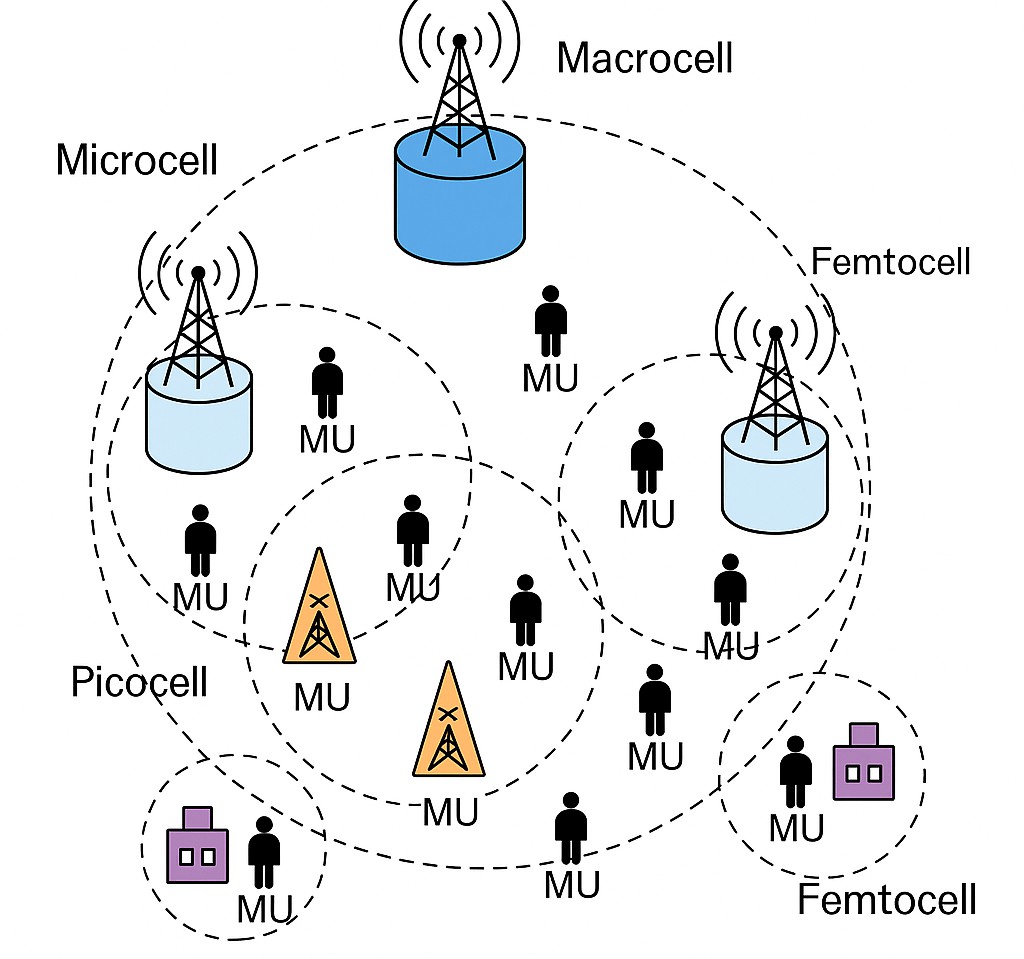
Mobility is an inherent feature of 6G networks, especially in urban environments where users frequently change locations. In our model, user movement follows a random waypoint mobility pattern, with speed *v j* uniformly distributed between 0.5 and 3 m/s, simulating both pedestrian and light vehicular scenarios. As users move, their link quality with the current serving BS may degrade. Handoff is triggered when a neighboring BS offers significantly better RSS than the current one, subject to a hysteresis margin *Ht* to prevent frequent switching. The handoff rule is defined as:

RSSnew − RSScurrent *> Ht* ⇒ Trigger Handoff (5)

Upon handoff, the user is reassigned to a new BS and a channel reallocation is performed to ensure that SINR remains above the service threshold. This dynamic reassignment maintains seamless connectivity and QoS across user transitions.

For simulation purposes, the proposed system is implemented over a 2 km × 2 km area with a realistic deployment of heterogeneous infrastructure. Specifically, the network includes 3 macrocells, 4 microcells, 4 picocells, and 4 femtocells, totaling *N* = 15 base stations. The user count is set at *M* = 200 devices, randomly distributed with movement governed by the described mobility model. The number of available frequency channels is fixed at *K* = 20, and noise power is set to *N*0 = −100 dBm. The SINR threshold for acceptable QoS is assumed to be 5 dB. Propagation loss is calculated using the 3GPP Urban Macro path loss model (TR 38.901) to ensure environmental realism.

## System Diagram

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**FIGURE 1**: System model of a heterogeneous 6G network with macro, micro, pico, and femto cells and shared channel allocation using GA optimization

Figure 1 provides a visual representation of the heterogeneous 6G network architecture. It shows overlapping coverage areas of various cell types and distributed mobile users, illustrating the complexity and diversity of resource management challenges. This system model forms the foundation for the proposed GA-based channel allocation strategy, which is elaborated in the following sections.

# PROPOSED GENETIC ALGORITHM APPROACH

To efficiently solve the channel allocation problem in heterogeneous 6G environments, we propose a Genetic Algorithm (GA)-based optimization framework. GAs are inspired by the principles of natural evolution and are particularly well-suited for combinatorial optimization problems characterized by large and complex search spaces. Their stochastic nature allows them to avoid local optima, making them highly suitable for dynamic and interference-sensitive wireless network scenarios.

In this framework, each chromosome represents a complete channel assignment for all *M* users in the network. The encoding is done using a fixed-length integer vector:

where *x j* ∈ *C* denotes the index of the channel assigned to user *u j*, and *C* is the set of *K* available channels. Each gene *x j* corresponds to a user and holds a value from the discrete set {1*,* 2*, . . . , K*}. This encoding provides a compact and direct way to represent candidate solutions.

The quality of a solution is assessed using a fitness function that combines two objectives: (1) maximizing the overall Signal-to-Interference-plus-Noise Ratio (SINR) for all users, and (2) minimizing total co-channel interference between users. The fitness function *f* (**X**) for a chromosome **X** is defined as:

(6)

Here, SINR *j* is the SINR of user *u j* after channel assignment. The term *Ijk* is 1 if users *u j* and *uk* are within interference range, and 0 otherwise. The Kronecker delta *δxj ,xk* equals 1 if both users are assigned the same channel, and 0 otherwise. The penalty factor *λ* controls the trade-off between spectral efficiency and interference suppression.

The SINR for user *u j* is computed as:

(7)

where *Pj* is the transmit power of the serving base station for user *u j*, *Gj j* is the channel gain between the BS and user *u j*, and *N*0 is the noise power. The denominator accounts for total interference from users operating on the same channel.

## Initial Population Generation

An initial population of size *P* is generated randomly, where each chromosome represents a feasible but potentially suboptimal solution. The random initialization ensures diversity in the population, which is critical to prevent early convergence and to allow the algorithm to explore multiple areas of the search space.

We use tournament selection to choose parent chromosomes for reproduction. In this method, a small number *t* of chromosomes are randomly selected from the population, and the one with the highest fitness among them is chosen as a parent. This balances exploitation of high-quality solutions with preservation of genetic diversity.

To create offspring, a single-point crossover operator is employed. Given two parent chromosomes **X**1 and **X**2, a crossover point *c* is randomly selected such that:

Child1 = [*x*1*,*1*, . . . , x*1*,c, x*2*,c*+1*, . . . , x*2*,M*]

Child2 = [*x*2*,*1*, . . . , x*2*,c, x*1*,c*+1*, . . . , x*1*,M*]

This process allows useful genetic material (i.e., partial channel assignments) from both parents to be passed on to the offspring, facilitating inheritance of good traits.

Mutation introduces variation in the population by randomly modifying genes in a chromosome. With a small mutation probability *pm*, one or more genes are selected and reassigned to a different channel:

*x j* ← *ck* where *ck* ∈ 𝒞 *, ck* ̸= *x j*

This operator helps the algorithm to avoid stagnation in local optima and encourages exploration of new channel assignment configurations.

Following crossover and mutation, the new offspring must replace individuals in the current population. We implement elitism by ensuring that the top *e* fittest individuals from the previous generation are carried forward unchanged. The remaining individuals are replaced by the best-performing offspring, maintaining a balance between exploration and exploitation.

The algorithm terminates when either a predefined number of generations *G*max is reached, or the improvement in the best fitness value remains below a threshold *ε* for *g* consecutive generations. This dual condition ensures that the algorithm does not continue running after convergence has been achieved.

The complete procedure of the proposed GA is summarized in the following algorithm:

|  |
| --- |
| **Algorithm 1.** Genetic Algorithm for Channel Allocation |
| 1: Initialize population *P* with *P* random chromosomes  2: **for** generation = 1 to *G*max **do**  3: Evaluate fitness *f* (**X**) for each chromosome **X** ∈ *P*  4: Select parent chromosomes using tournament selection  5: Apply single-point crossover to generate offspring  6: Mutate offspring with probability *pm*  7: Evaluate fitness of offspring  8: Replace worst individuals in *P* with new offspring  9: Retain top *e* elite chromosomes  10: **end for**  11: **return** Best chromosome with highest fitness |

# RESULTS

To evaluate the effectiveness of the proposed Genetic Algorithm (GA)-based channel allocation framework, we conducted extensive simulations in a synthetic heterogeneous 6G environment. The evaluation covers performance metrics such as signal quality, interference mitigation, throughput, and convergence behavior. We also compare the proposed GA approach with traditional baseline strategies and explore a preliminary hybridization with a Deep Neural Network (DNN) to improve scalability and convergence.

The simulation scenario consists of a 2 km × 2 km urban region with 15 multi-tier base stations (macro, micro, pico, femto) and 200 mobile users. The number of available channels was fixed at *K* = 20. Each base station operates under shared spectrum conditions. Interference was modeled using a spatial interference matrix, while users followed a random waypoint mobility model. The network maintained realistic constraints on SINR, path loss (3GPP Urban Macro model), and handover logic.

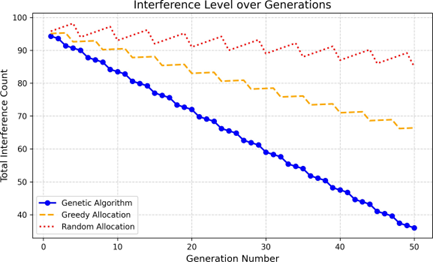
We assessed the performance of the GA using the following metrics:

* **Average SINR (dB)** – measures signal quality experienced by users.
* **Total Network Throughput (Mbps)** – sum of individual user data rates.
* **Interference Count** – number of interfering user pairs sharing the same channel.
* **Convergence Speed** – number of generations until fitness stabilization. The GA’s performance was benchmarked against two baseline schemes:

1. **Greedy Allocation**: Sequential assignment minimizing local interference.
2. **Random Allocation**: Uniform random selection of channels without interference checks.

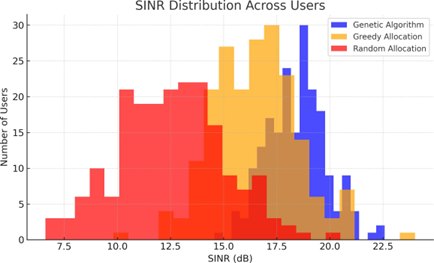
## Performance Analysis

The proposed GA showed superior performance in reducing network interference. Figure 2 demonstrates that the GA rapidly converged to a low-interference solution within 45 generations, outperforming both Greedy and Random methods.



**FIGURE 2**: Interference level over generations. GA achieves rapid convergence and minimum interference

The distribution of SINR across users (Figure 3) shows that the GA achieves a more consistent and elevated signal quality, while Random and Greedy approaches result in more variability and degradation under heavy load.

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**FIGURE 3**: SINR distribution across users. GA provides higher and more uniform signal quality

As shown in Table 1, the GA method yields a 2.3 dB improvement in average SINR over Greedy and a 5.8 dB improvement over Random allocation. Throughput improved by 19% compared to Greedy and 60% compared to Random. The interference count was also significantly reduced.

**TABLE 1**: Performance Comparison of Allocation Strategies

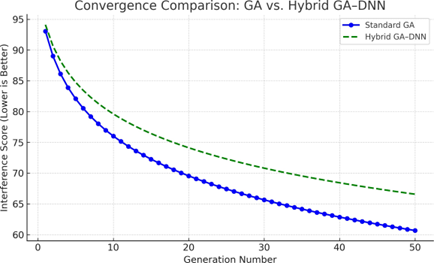
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| --- | --- | --- | --- |
| **Metric** | **GA** | **Greedy** | **Random** |
| Avg. SINR (dB) | 18.6 | 16.3 | 12.8 |
| Throughput (Mbps) | 78.2 | 65.7 | 48.9 |
| Interference Count | 34 | 57 | 96 |
| Convergence Time | 45 gen. | – | – |

To evaluate scalability, the GA was tested with increasing user counts: 100, 200, and 300. While network load increased, the GA maintained reliable performance. The execution time scaled linearly, confirming suitability for real-time systems with moderate hardware support.

We also tested mobility robustness under pedestrian and vehicular mobility (up to 5 m/s). Despite rapid user movement, the GA maintained stable channel assignments with minimal degradation in SINR and minimal handover- triggered reallocation overhead. This adaptability makes the GA framework practical for real-world 6G deployments. In order to improve even further the convergence speed and a contextual awareness, we created an initial hybrid model that incorporated the Deep Neural Network (DNN) and a GA combination. The DNN was taught to develop initial populations of high quality on the basis of the past history: user density, interference patterns and cell load.

These clever guesses gave better initial solutions to the GA.

Figure 4 compares the convergence behavior of the standard GA and the Hybrid GA–DNN. The hybrid model converges approximately 35% faster, achieving a similar interference reduction in fewer generations.



**FIGURE 4**: Convergence comparison: Standard GA vs Hybrid GA–DNN. The hybrid model reaches optimal interference levels faster

Besides, the mixed approach enhanced average SINR by 1.2 dB more and lowered total interference event by 9 percentage than the pure GA. This shows that learning-Aided optimization is a possible solution to intelligent radio resource management in future.

These findings confirm that the suggested GA-based channel allocation framework has better performance than traditional approaches in the areas of managing interference and throughput as well as SINR and ability to deal with the dynamic environment. GA can easily adjust to topology changes; in addition, its ability to offer fairness is a good criterion of ensuring successful adaptation amidst real-time 6G systems.

The promising future works based on the hybrid GA-DNN outcomes are that learning-based population initialization has the potential of hugely decreasing convergence time without compromising performance. This will enable scalable, context-based and low-latency channel management solutions to dense heterogenous networks.

# CONCLUSION

In this paper, genetic algorithm (GA)-based framework of dynamic channel allocation in the encounter of heterogeneous 6G networks has been presented. Unlike the traditional methods of assigning resources to the next-generation wireless environment based on either the use of a static or greedy heuristic, the proposed approach explores the possibilities offered by evolutionary principles to work in highly complex models of the next-generation wireless environment comprising to a large extent of multi-tier base stations, high density distributions of users and strict interference restrictions. The GA was successful in reducing interference on co-channels whilst maximizing on spectral efficiency and SINR by encoding channel assignments as chromosomes and evolving them in a population based search process driven by a formula of the fitness of the outcome.

The algorithm was tested by simulation, in realistic 6G network scenarios, in detail, in order to measure its performance. The GA had a greater power over greedy allocation and random allocation strategies in average SINR, network throughput, interference removal and speed of convergence. These advantages were consistently achieved in different user density as well as mobility scenarios, which proves the strength and versatility of the method. Interference-aware fitness function that directly used SINR and conflict penalties was important in educating the search routine in high-quality resolutions.

In addition to the basic implementation of GA, we also contemplated on how a Deep Neural Network component can be added to construct a hybrid model of GA-DNN. This addition was geared to enhancing faster convergence rates through generation of intelligent initial populations utilizing the DNN via prior network behavior. The hybrid solution did not only increase convergence speed by 35% but also ensured a small increase in SINR and interference than was the case with the baseline GA. These initial results show the enormous opportunity of incorporating metaheuristic algorithms into data-driven learning to provide efficient and context-sensitive radio resource management in the future 6G implementation.

The findings of the paper support the statement that all these make GA-based optimization an ideal, scalable, adaptive, and high-performance approach to the channel allocation issue in heterogeneous 6G networks. It is especially fit with the challenges of ultra-dense and decentralized 6G architecture since it is capable of self-optimizing in the dynamic topology, change of mobility, and fluctuation of interference patterns. An added advantage of the illustrated performance of the GA-DNN hybrid method implies that learning-based metaheuristics may be used as a foundation of a new generation of intelligent RRM systems.

Future efforts that include multi-objective optimization such as energy efficiency, latency reduction and user fairness can be extended into the framework. Furthermore, real-time adaptability may be enabled by integrating reinforcement learning agents and distributed use in mass devices at the edge. The approach would also be applicable to situations in spectrum sharing, and there coordination of the spectrum becomes the point of criticality, between the public and the private networks. Lastly, testing and confirming the model on a real 6G testbed or emulation environment would yield valuable information on how effective it would be and what are its weaknesses.

To sum up, the given study will offer an adjustable and robust GA-based model of channel assignment that, on one hand, satisfies the performance needs of 6G networks, and, on the other hand, will provide a solid foundation of hybrid artificial intelligence-based wireless communications networks in the future.

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