

Research on Communication Signal Coverage Methods Based on Recursive Genetic Algorithms

Sheng Ye^{1,*}, Fuchun Huang¹

¹School of Information Technology & Engineering, Guangzhou College of Commerce, Guangzhou 511363, Guangdong, China

Abstract

The availability of communication signals for dense wireless local area networks (WLANs) is being increasingly hindered by spectrum contention, interference, and traffic dynamics. Side effects of coverage can also be captured by higher layers, such as the transport or application layer; however, their sensing capabilities are limited, and their information may be strongly biased by the network conditions or the user traffic. In this paper, we explore a coverage-quality-aware optimization framework based on Recursive Genetic Algorithm (RGA) for multi-basic service set (BSS) WLAN environments. Signal coverage is considered as coverage quality and is then evaluated in an indirect manner using network layer performance metrics, namely throughput, packet delay, and control-frame reliability, which is measured using RTS frame loss. A private four-BSS spectrum management dataset produced by the Komondor WLAN simulator is utilized to test potential spectrum configurations. The suggested RGA refines the elite solutions to the maximum spectrum allocation iteratively under interference-aware scenarios. Experimental results demonstrate that the RGA outperforms static allocation, random selection, and the standard GA, with a best average throughput of 0.529, a lowest packet delay of 0.004, and a minimum RTS frame loss of 0.0065. Convergence and Pareto-based analyses further establish the stability as well as the multi-objective nature of the proposed approach. The results confirm that the dataset-driven design of the multi-BSS WLAN optimization by using network-level performance metrics plays a key role in providing a generalizable and reproducible tool for enhancing coverage quality of WLAN networks.

Keywords: Recursive Genetic Algorithm, Signal Coverage Optimization, Multi-BSS WLAN, Spectrum Management, Network Performance Evaluation

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*Corresponding author. Email: shengye0215@outlook.com, yesheng2110171@163.com

1. Introduction

The spectacular rise of wireless local area networks (WLANs) has aggravated the situation regarding the use of the spectrum, especially in cases of heavy usage where several BSSs share the same frequency channels and coexist [1]. In these kinds of situations, reliable communication is not only about the strength of the signal

but also about the network's capability to keep the performance at levels of throughput, latency, and control signalling under interference and traffic load variations [2][3]. Thus, the traditional physical-layer coverage metrics can no longer fully describe the effective usability of wireless coverage in the practical WLAN scenario [4]. Physical-layer metrics such as Received Signal Strength Indicator (RSSI) and Signal-to-Interference-plus-Noise Ratio (SINR) provide insight into signal propagation

characteristics, they do not fully capture the actual user experience in dense multi-BSS WLAN environments. In such scenarios, network performance is strongly influenced by interference, contention, and traffic dynamics, which are not reflected by signal strength alone. Therefore, network-layer metrics such as throughput, packet delay, and control-frame reliability are preferred, as they directly represent the efficiency and reliability of communication under realistic operating conditions.

Recent studies start viewing signal coverage more and more through the lens of performance. Coverage quality is measured using network-layer indicators such as throughput, packet delay, and packet or control-frame loss [5]. The combined effect of these metrics indicates the wireless connectivity that is the most available, stable, and reliable for the users, particularly in the areas where the spectrum is shared [6] [7]. In the management of the spectrum and the optimization of interference-aware WLANs, such performance-based indicators are widely used as proxy measures of coverage effectiveness [8] [9].

The reason why genetic algorithms (GAs) have been the choice of researchers for wireless optimization problems is their ability to find good solutions in complex, non-linear, and multi-objective scenarios [10] [11]. Nonetheless, traditional GAs often led to slow convergence and getting stuck at local optima when used on very large spectrum configuration spaces [12]. To solve these problems, we present an RGA in this paper that employs elite solution preservation and recursive refinement to boost both convergence speed and solution stability [13] [14].

In the present work, signal coverage is viewed as a quality of coverage rather than just physical-layer propagation coverage. The quality of coverage is assessed indirectly by means of the network-layer performance metrics of throughput, packet delay, and reliability of control frames measured using RTS (Request to Send) frame loss. The metrics of the physical layer, such as RSSI (Received Signal Strength Indicator) or SINR (Signal to Interference plus Noise Ratio), are not taken into account explicitly because the spectrum management efficiency is the main concern under the conditions of interference and traffic load. A self-contained four-BSS spectrum management dataset created with the help of the Komondor wireless network simulator is used to make sure that the entire evaluation is reproducible and comprehensive across all spectrum configuration combinations.

A Recursive Genetic Algorithm (RGA) incorporating a recursive elite refinement mechanism is proposed to enhance convergence stability and solution quality in multi-BSS WLAN spectrum allocation. The framework employs dataset-driven multi-objective optimization based on throughput, packet delay, and RTS frame loss to achieve effective interference-aware spectrum management.

The proposed framework enhances spectrum allocation efficiency in interference-prone multi-BSS WLAN environments through improved optimization stability and balanced network performance. By simultaneously optimizing throughput, packet delay, and RTS frame loss, the framework contributes to improved communication

reliability and more effective wireless network management.

Although genetic algorithms are widely applied to WLAN spectrum allocation, the novelty of this study does not lie in the use of a genetic algorithm itself. Instead, the proposed RGA introduces a recursive elite refinement mechanism that repeatedly performs localized mutation, re-evaluation, and reintegration of high-quality solutions across generations. This mechanism enhances the exploitation of promising spectrum configurations while maintaining global exploration through crossover and adaptive mutation. This design distinguishes RGA from the standard GA by explicitly coupling global evolutionary exploration with repeated local exploitation of elite solutions, providing a targeted mechanism for improving convergence stability and solution quality in the evaluated multi-BSS WLAN spectrum optimization problem.

Beyond the practical performance gains, the proposed RGA provides a conceptual advancement by integrating recursive elite refinement into the conventional evolutionary search process, enabling repeated local exploitation of promising spectrum configurations while preserving global exploration.

The main contributions of this work are as follows:

- (i) A Recursive Genetic Algorithm (RGA) with a recursive elite refinement mechanism for multi-BSS WLAN spectrum allocation, enabling repeated refinement and re-evaluation of high-quality spectrum configurations.
- (ii) A methodology for coverage-quality evaluation based on performance that employs network-layer indicators;
- (iii) A dataset-driven optimization approach that allows reproducible and systematic evaluation; and
- (iv) Extensive comparative analysis demonstrating the performance of the proposed method against static, random, and standard GA-based methods.

2. Literature Review

In their study, Polak et al. [15] introduced a budget-friendly and easy-to-handle measurement setup for assessing the coverage of 4G and 5G mobile signals in a factory environment where signals could be very complex. They also performed recording of all the key performance indicators for both the downlink and uplink in a long-term campaign, thus making the dataset accessible for reproducibility purposes. Selvaraj et al. [16] proposed a method of using a phase-reconfigurable combined-loop metasurface for the new generation of reconfigurable intelligent surfaces (RISs) that are low-power, friendly to the environment, and very effective in communication. The method utilized four PIN diodes forming the 2×2 periodic arrays, thus allowing 16 different phase reflection states. Moreover, the design was verified through both numerical simulations and experiments on a 32×32 metasurface. Xiang and Wang [17] provided an approach based on a

distributed sensor network to determine the level of 5G mobile signal coverage, thus providing a solution to some of the drawbacks of traditional road-testing methods. Their approach made a remarkable contribution to wireless sensor network coverage by collecting the received signal strength through randomly located sensor nodes, optimizing a neural network with an advanced particle swarm optimization, and interpolating the coverage in areas where the signal was not detected. Chrysikos et al. [18] designed an RF coverage for a 5G smart city network to support the real-time health monitoring of patients living in homestays during emergency situations. Their method found the optimal placement of antennas for outdoor metropolitan areas analytically, incorporating the propagation conditions inside buildings for uplink channels using the digital baseband signaling appropriate for health monitoring services. Guo et al. [19] suggested an upgraded perception model for the coverage of the WSN that includes path loss and false alarm probability, with the aim of reflecting the signal transmission characteristics in the real world more realistically.

Nemer et al. [20] put forward a distributed control strategy which employs UAVs as mobile base stations for the improvement of wireless coverage in changing environments like transportation systems and disaster situations. Their proposed method, referred to as state-based game with actor-critic (SBG-AC), simulates UAV interactions through a state-based potential game and combines the actor-critic algorithm for convergence, learning, and distributed control. Shao et al. [21] proposed a multi-AP cooperative radio resource allocation method for IEEE 802.11be WLANs to mitigate co-channel interference in dense deployment scenarios. Their approach jointly considers resource allocation and interference avoidance to improve network throughput. Zhang et al. [22] investigated throughput optimization in IEEE 802.11be networks using multi-link operation and AP coordination, with emphasis on resource allocation, spectrum reuse, and performance improvement in dense WLAN environments. Park et al. [23] conducted a survey on IRS-assisted UAV communication systems and pointed out the different ways IRSs can improve the performance of UAV networks in terms of spectral efficiency, energy efficiency, and safety. They identified six representative scenarios of deployment and evaluated the existing state of the art including machine learning approaches for performance enhancement. Hassan et al. [24] suggested a user association algorithm with dynamic multi-band capability that would make it possible to connect coexisting RF, mmWave, and THz networks for 6G applications. The algorithm continually assesses the actual channel conditions, and users are periodically reassigned to equilibrate network load considering in link quality, blockage risk, and user priority.

Yang et al. [25] presented a comprehensive overview of mmWave antenna technologies for 5G systems, stressing their essential contributions to the development of high-speed and low-latency communication. Various elements of the study, like antenna types, MIMO architectures,

beamforming techniques, and integration methods like antenna-in-package and chip-level integration together with materials and fabrication processes, were analyzed. Vizzarri et al. [26] took next-generation railway communication systems into consideration, particularly ACS and FRMCS, which interconnect 4G/5G terrestrial networks and HTS LEO constellations. Chen and Liang [27] provided a solution to the problem of moving object coverage in mobile wireless sensor networks with a limited number of sensing nodes by optimizing the mobility of the sensors. The researchers made use of GA and discrete particle swarm optimization (DPSO) to determine efficient trajectories with the objective of minimizing total movement as well as balancing the residual energy of the nodes. Wang et al. [28] introduced a method for reducing noise in the monitoring of PD in mining cables that consisted of the optimization of VMD through GA followed by wavelet thresholding. The GA did the optimization of the VMD parameters, which led to the extraction of intrinsic mode functions (IMFs); after that, the IMFs were denoised and constructed once again in order to enhance the SNR. Li et al. [29] presented a quantum genetic algorithm (QGA) based task scheduling algorithm for the processing of heterogeneous signals on platforms that sought to improve efficiency and reduce computational cost. The method consists of mapping tasks onto qubits, employing chromosome coding based on quantum coherence, and performing full-interference crossover and quantum rotation gates in order to circumvent local optima.

Genetic algorithm-based optimization techniques have been widely explored in communication network design and wireless infrastructure planning. Li et al. [30] proposed an improved genetic algorithm for communication base station site selection, demonstrating the effectiveness of evolutionary approaches in optimizing coverage-oriented deployment in communication networks. Similarly, Ussipov et al. [31] introduced a maximum-entropy genetic algorithm for router node placement in wireless mesh networks, highlighting the capability of entropy-driven evolutionary strategies in improving network connectivity and resource distribution. In addition, Kim et al. [32] investigated cross-technology interference-aware rate adaptation in time-triggered wireless local area networks, emphasizing the role of intelligent adaptation mechanisms in mitigating interference and enhancing WLAN performance. These studies collectively indicate the growing relevance of genetic algorithm-based and interference-aware optimization methods for improving communication signal coverage and network efficiency in complex wireless environments.

Tejedor-Romero et al. [33] investigated optimization-based channel assignment in dense Wi-Fi networks to reduce interference and improve channel allocation efficiency, while Soufi et al. [34] proposed a PSO-based dynamic channel allocation approach for IEEE 802.11 WLANs to minimize co-channel interference. These studies demonstrate the effectiveness of optimization and metaheuristic techniques for improving channel

management and network performance in dense WLAN environments.

Unlike conventional spectrum allocation approaches and standard genetic algorithms, the proposed RGA introduces a recursive elite refinement mechanism that continuously improves high-quality solutions across generations. While standard GA and other heuristic methods such as PSO and DPSO primarily rely on population-based exploration, they often suffer from slow convergence and local optima stagnation. In contrast, RGA integrates adaptive mutation and recursive feedback to enhance convergence speed and solution stability. Moreover, existing multi-BSS optimization studies typically focus on single-objective or simulation-based evaluation, whereas the proposed method performs dataset-driven multi-objective optimization using throughput, delay, and RTS frame loss. This distinction enables RGA to achieve more balanced and robust spectrum configurations under interference-aware WLAN environments.

The proposed RGA extends the conventional genetic algorithm through recursive elite refinement, where high-quality solutions are iteratively improved and re-evaluated before reintegration into the population. This mechanism enhances convergence stability and solution quality while enabling dataset-driven multi-objective spectrum optimization using throughput, packet delay, and RTS frame loss in multi-BSS WLAN environments.

Limitations

Polak et al. [15]: This work is dedicated to signal performance metrics exclusively and does not take into account mobility patterns or characterization of the interference sources.

Selvaraj et al. [16]: The suggested metamaterial is assessed only through controlled simulations and experiments, and not by means of validation in real-world propagation environments.

Xiang and Wang [17]: The coverage evaluation technique is entirely simulation-based and does not get validated in intricate real-world deployment scenarios.

Chrysikos et al. [18]: The RF coverage design is carried out through an analytical and simulation-based approach, and no field measurements are done for performance verification.

Guo et al. [19]: The superior coverage model is validated through simulations only, with no experimental testing in real-world environments.

Nemer et al. [20]: The UAV-based coverage enhancement strategy is explored only through simulations and lacks the real-world deployment validation aspect.

Shao et al. [21]: The proposed multi-AP cooperative radio resource allocation method for IEEE 802.11be WLANs focuses on mitigating co-channel interference, but its evaluation is based on the considered simulation and configuration settings, leaving further validation under diverse and dynamic WLAN deployment conditions as an open issue.

Zhang et al. [22]: The IEEE 802.11be throughput optimization approach considers multi-link operation and AP coordination; however, further evaluation under highly dynamic traffic, interference, and large-scale dense WLAN environments is required to assess its broader practical applicability.

Park et al. [23]: The research is a survey that gives theoretical insights and does not provide new experimental or simulation-based performance evaluations.

Hassan et al. [24]: The multi-band user association algorithm is only proven through simulations, and there is no experimental evaluation in actual 6G networks.

Yang et al. [25]: The review shows the theoretical and design aspects of mmWave antennas, and there is no experimental benchmarking in real deployments.

Vizzarri et al. [26]: The assessment of railway communication is based upon simulations that employ public data and do not pass field trials for validation.

Chen and Liang [27]: The optimization of sensor mobility is judged only by means of simulations and not through the actual deployment of mobile sensors for validation.

Wang et al. [28]: The suggested GA-based denoising method is restricted in its application and has not been extended to other industrial signal environments.

Li et al. [30]: The quantum genetic algorithm was tested only on synthetic task graphs while not being implemented on real heterogeneous processing platforms.

Li et al. [30]: The genetic algorithm for base station site selection is validated mainly through simulations, without real-world large-scale deployment testing.

Ussipov et al. [31]: The maximum-entropy genetic algorithm for router placement focuses on mesh topology optimization and lacks evaluation under dynamic WLAN interference conditions.

Kim et al. [32]: The interference-aware rate adaptation method is tested in controlled WLAN environments, with limited consideration of heterogeneous traffic and large-scale deployments.

It is still common to conduct evaluations by simulations only, check a single performance criterion, or work without adaptive evolutionary optimization in most studies. Besides, there is still little research done on recursive genetic frameworks used for dataset-driven multi-BSS spectrum optimization.

3. Methodology

The complete methodological workflow of the proposed RGA for optimizing communication signal coverage in a multi-BSS WLAN environment is depicted in Figure 1. Initially, the 4-BSS WLAN dataset is completely self-contained; it represents a variety of spectrum configurations and network performance measures. The dataset has to go through data preprocessing and normalization as a first step, in order to make throughput, delay, and RTS frame loss values comparable.

Then, only the most important spectrum parameters are changed into chromosome representations, making it ready for evolutionary optimization. A multi-objective fitness function, defined in terms of the normalized throughput, packet delay, and RTS frame loss, is used to evaluate the quality of a candidate solution. The core optimization is done by an RGA that uses selection, crossover, mutation, and recursive elite refinement to not only speed up convergence but also ensure that the solution is stable.

The algorithm produces an optimized spectrum configuration, which is later tested through dataset-based simulation in order to derive performance metrics. A comparative analysis is performed against static allocation, random allocation, and standard genetic algorithm methods.

The Pareto frontier is constructed by evaluating all candidate spectrum configurations explored by the RGA and identifying the subset of non-dominated solutions based on throughput, delay, and RTS frame loss. The final RGA-selected configuration is observed to lie on this Pareto frontier, indicating a balanced trade-off among competing objectives. Given in Eqn. (1)

$$\mathbf{x}_i < \mathbf{x}_j \Leftrightarrow \begin{cases} T_i \geq T_j \\ D_i \leq D_j \\ L_i \leq L_j \end{cases} \text{ and at least one inequality is strict} \quad (1)$$

Where:

- T = average throughput
- D = average packet delay
- L = RTS frame loss ratio

A solution $\mathbf{x}_i$ is said to dominate $\mathbf{x}_j$ if it achieves no worse performance across all objectives and strictly improves at least one objective. The set of all non-dominated solutions constitutes the Pareto-optimal frontier.

Finally, result validation is performed using cumulative distribution functions (CDFs), per-BSS performance analysis, and Pareto trade-off evaluation, where non-dominated solutions are formally identified based on multi-objective dominance criteria.

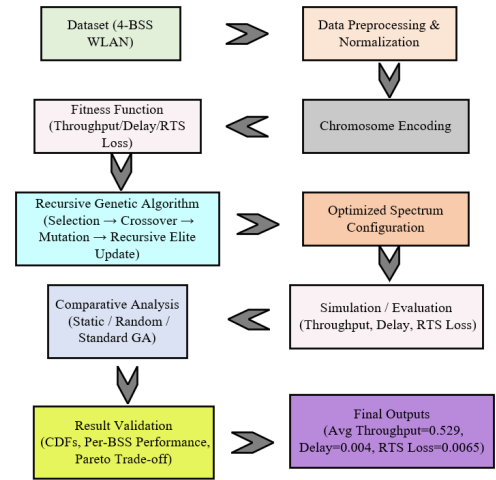


Figure 1. Workflow of the Proposed RGA –Based Communication Signal Coverage Optimization Framework

3.1 Dataset Description

This study employs a self-contained 4-BSS spectrum management dataset [35] generated using the Komondor wireless network simulator. The dataset exhaustively enumerates all feasible spectrum management configurations for a dense WLAN deployment. The dataset is generated using the Komondor WLAN simulator under a controlled multi-BSS environment consisting of four BSSs, each with one access point and multiple associated stations deployed in proximity to create overlapping coverage and realistic interference. A saturated traffic model is assumed, where all stations continuously transmit data to emulate high-load conditions. Interference is modeled through overlapping channel assignments, capturing both co-channel and adjacent-channel effects. The channel behavior follows standard IEEE 802.11 propagation characteristics, including path loss and attenuation, whose impact is implicitly reflected in the network performance metrics. The four-BSS configuration is selected to balance realistic interference representation and computational feasibility, enabling exhaustive evaluation of spectrum configurations while maintaining reproducibility.

The dataset consists of 4096 spectrum configurations, where each configuration represents a unique combination of channel, bandwidth, and traffic load across four BSSs. Each configuration corresponds to one sample, resulting in 4096 total dataset instances generated using the Komondor simulator. Each dataset instance represents a global configuration consisting of four BSSs, where each BSS operates under specific channel and bandwidth settings while experiencing mutual interference.

The employed dataset does not include physical-layer signal measurements such as received RSSI, signal-to-

interference-plus-noise ratio (SINR), path loss, or node location information. As a result, the suggested method does not intend to simulate the physical signal propagation. It, rather, works on the optimization of coverage quality at the MAC and network layers by means of spectrum configuration, where throughput, packet delay, and control-frame reliability are treated as indicators of effective wireless coverage under interference and traffic load conditions. The employed dataset represents a controlled set of offline spectrum configurations generated using the Komondor simulator. Although it enables reproducible and systematic evaluation of the proposed optimization framework, it does not fully represent the temporal variability of WLAN traffic and interference conditions. Therefore, the present study evaluates the optimization capability under predefined network conditions rather than claiming direct adaptation. For practical deployment, the framework can be extended through periodic dataset updates or online optimization using current network measurements to adapt spectrum configurations to changing traffic and interference conditions.

In practical WLAN deployments, the precomputed configuration entries can be periodically updated using current network measurements or simulation outputs to support adaptive spectrum optimization. The present study focuses on offline optimization using predefined network conditions, while cost-function evaluation is considered as a direction for future validation.

Input Parameters:

For each BSS $b \in \{1, 2, 3, 4\}$, the following parameters are defined:

- Primary Channel: Given in Eqn. (2)

$$c_b \in \{c_1, c_2, \dots, c_M\} \quad (2)$$

- Maximum Bandwidth Index: Given in Eqn. (3)

$$w_b \in \{20, 40, 80\} \text{MHz (indexed)} \quad (3)$$

- Traffic Load: Given in Eqn. (4)

$$\lambda_b \text{ [packets/s]} \quad (4)$$

3.2 Performance Metrics

Network-level coverage quality is indirectly evaluated through the following network-level performance metrics:

- Throughput
- Packet Delay
- RTS Frame Loss Ratio

To evaluate the overall system performance, network-level averages are computed as given in Eqn. (5)

$$\bar{T} = \frac{1}{4} \sum_{b=1}^4 T_b, \bar{D} = \frac{1}{4} \sum_{b=1}^4 D_b, \bar{L} = \frac{1}{4} \sum_{b=1}^4 L_b \quad (5)$$

Definition of Signal Coverage:

Network-level coverage quality is defined as the ability of a WLAN configuration to sustain high throughput, low packet delay, and reliable control-frame delivery under interference and traffic-load conditions. In this study, throughput, packet delay, and RTS frame loss are used as network-level performance indicators to assess communication quality. These metrics capture the effects of interference and channel contention on WLAN performance but do not directly measure physical-layer signal propagation or geographical coverage. Therefore, the proposed coverage-quality measure represents network-level communication performance rather than direct physical signal coverage. Physical-layer indicators such as RSSI and SINR are not included because they are unavailable in the employed dataset. Therefore, the proposed coverage-quality metric is intended to represent network-level communication performance under interference and traffic-load conditions rather than direct physical-layer signal coverage.

A formal and quantitative interpretation: Network-level coverage quality is defined as a composite metric that integrates normalized network-layer performance indicators. Let the normalized throughput, packet delay, and RTS frame loss be denoted as T_m, D_m , and L_m , respectively. The overall network-level coverage-quality score Q_c is formulated as given in Eqn. (6):

$$Q_n = \alpha - T_n + \beta \cdot (1 - D_n) + \alpha \cdot (1 - L_n) \quad (6)$$

where $\alpha, \beta, \gamma \in [0, 1]$ are weighting coefficients satisfying $\alpha + \beta + \gamma = 1$.

In this formulation, throughput is directly proportional to coverage quality, whereas packet delay and RTS frame loss are inversely related to effective coverage. The normalization ensures that all metrics are mapped onto a comparable scale, preventing dominance of any single metric. This definition explicitly links Network-level coverage quality to network-layer performance by capturing three essential characteristics of wireless communication: data transmission efficiency, latency performance, and control-frame reliability.

A higher value of Q_c indicates superior coverage quality under interference-aware multi-BSS conditions. The resulting score represents network-level communication performance and is not intended to quantify physical signal coverage.

4. Data Preprocessing

4.1 Metric Normalization

Since throughput, delay, and RTS loss operate on different scales, min-max normalization is applied, as given in Eqn. (7)

$$\begin{aligned} T' &= \frac{T - T_{\min}}{T_{\max} - T_{\min}} \\ D' &= \frac{D - D_{\min}}{D_{\max} - D_{\min}} \\ L' &= \frac{L - L_{\min}}{L_{\max} - L_{\min}} \end{aligned} \quad (7)$$

This ensures numerical stability and prevents metric dominance during optimization.

4.2 Feature Selection and Aggregation

Only spectrum-relevant parameters are retained: Given in Eqn. (8)

$$\mathbf{x} = [c_1, w_1, \lambda_1, \dots, c_4, w_4, \lambda_4] \quad (8)$$

Per-BSS metrics are aggregated into network-level fitness indicators, enabling evaluation of global spectrum configurations rather than isolated links.

5. Recursive Genetic Algorithm (RGA)

The RGA used for optimizing the communication signal coverage) in a multi-BSS WLAN environment is illustrated in detail in Figure 2. In the beginning, the process creates an initial population of chromosomes representing possible spectrum configurations in the BSS area. Each chromosome enters the evaluation stage where its fitness is measured through normalized network performance metrics such as throughput, packet delay, and RTS frame loss.

After evaluation, a probabilistic selection process selects parent chromosomes, and through crossover, offspring solutions are produced. Then, a recursion-controlled adaptive mutation module is used to keep the population diverse and to prevent the occurrence of premature convergence. A combination of high-quality solutions is achieved through elite selection and recursive refinement processes, thereby making sure that the best chromosomes are kept and locally optimized across the generations that follow.

A stopping criterion is an indicator to assess whether the process has reached its end. If it fails to be accepted, the algorithm will continue with a process of recursively updating the generation, returning the best chromosomes to the group through a recursive elite injection mechanism, thus speeding up convergence and making the solution more stable. When the stopping condition is satisfied, the best chromosome is chosen as the final optimized spectrum configuration, resulting in the best solution with respect to increased throughput, reduced delay, and minimized RTS frame loss.

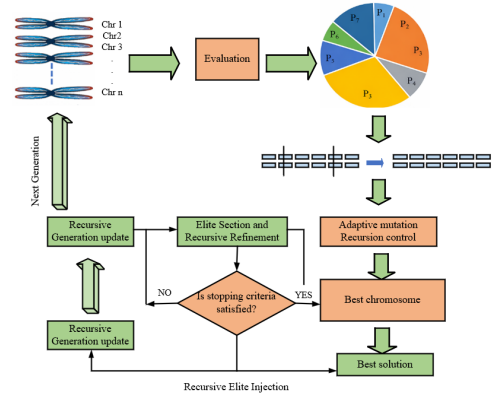


Figure 2. Architecture of the Proposed RGA for Communication Signal Coverage Optimization

5.1 Chromosome Encoding

Each chromosome represents a complete spectrum configuration across all BSSs. The chromosome is encoded as a fixed-length vector, as given in Eqn. (9)

$$\mathbf{C} = [c_1, w_1, \lambda_1, c_2, w_2, \lambda_2, c_3, w_3, \lambda_3, c_4, w_4, \lambda_4] \quad (9)$$

Each gene corresponds to a feasible dataset configuration. A chromosome representing a spectrum configuration for a four-BSS system can be expressed as: $\mathbf{C} = (c_1, c_2, c_3, c_4)$ where each gene c_i corresponds to the configuration of the i^{th} BSS, including its assigned channel index, bandwidth, and traffic load. For instance, a sample chromosome such as $\mathbf{C} = [(1,2,3), (2,1,2), (3,2,1), (1,3,2)]$ represents a complete network configuration where each tuple defines the operational parameters of an individual BSS. This representation allows the genetic algorithm to efficiently explore different spectrum allocation combinations.

5.2 Initial Population

An initial population: Given in Eqn. (10)

$$\mathcal{P}_0 = \{\mathbf{C}_1, \mathbf{C}_2, \dots, \mathbf{C}_N\} \quad (10)$$

is randomly sampled from valid dataset rows, ensuring all chromosomes represent physically realizable WLAN states. Population size is set to 50, crossover rate to 0.8, and mutation rate to 0.1 with adaptive reduction. Elite selection is 10% of the population. The algorithm runs for a maximum of 100 generations with a convergence threshold of 10^{-4} . These values are empirically chosen to balance convergence speed and solution quality.

The key evolutionary parameters of the proposed RGA are explicitly defined. The population size is set to 50 chromosomes, and the algorithm is executed for a

maximum of 100 generations. These parameters are consistently used across all experiments, including the standard genetic algorithm baseline, to ensure a fair and controlled comparison. The chosen values provide a balance between convergence speed and solution quality, as validated through preliminary experimentation. The maximum nominal number of population evaluations is 5,000; however, this does not imply 5,000 unique configurations because previously evaluated configurations may be revisited during the evolutionary process.

5.3 Fitness Function

The multi-objective optimization problem is scalarized into a weighted fitness function, as given in Eqn. (11)

$$\mathcal{F} = \alpha \cdot \bar{T}' - \beta \cdot \bar{D}' - \gamma \cdot \bar{L}' \quad (11)$$

Where:

- $\hat{T}$ = normalized throughput
- $\hat{D}$ = normalized packet delay
- $\hat{L}$ = normalized RTS frame loss
- $\alpha, \beta, \gamma \in [0,1]$ are weighting coefficients

The weighting coefficients α , β , and γ respectively determine how much throughput maximization, delay minimization, and reliability improvement are valued. To prevent one performance metric from being favored and to ensure that the multi-objective optimization is balanced, equal weights ($\alpha=\beta=\gamma=1/3$) are used. Sensitivity analysis indicates that the optimal solutions' ranking is not greatly affected by slight changes in these weights. The use of equal weights promotes a balanced optimization process by ensuring that no single performance metric dominates the fitness evaluation. In contrast, assigning higher weight to a specific metric could bias the search toward improving that objective at the expense of others, potentially leading to suboptimal overall network performance. By maintaining equal importance across all objectives, the proposed formulation encourages the exploration of solutions that achieve a fair trade-off and lie closer to the Pareto-optimal frontier.

5.4 Selection

Tournament selection is employed:

- Randomly select k chromosomes
- Choose the chromosome with maximum fitness:
Given in Eqn. (12)

$$\mathbf{C}_{\text{elite}} = \arg \max \mathcal{F} \quad (12)$$

This ensures selection pressure while maintaining diversity.

5.5 Crossover

A multi-point crossover operator exchanges spectrum segments between parents: Given in Eqn. (13)

$$\mathbf{C}_{\text{child}} = \text{Crossover}(\mathbf{C}_{p1}, \mathbf{C}_{p2}) \quad (13)$$

Crossover points align with BSS boundaries to preserve semantic consistency.

5.6 Adaptive Mutation

An adaptive mutation strategy is employed to promote exploration during early generations and refinement during later stages, thereby reducing premature convergence. Mutation probability p_m is dynamically adjusted: Given in Eqn. (14)

$$p_m(g) = p_m^{\min} + (p_m^{\max} - p_m^{\min}) \cdot \left(1 - \frac{g}{G}\right) \quad (14)$$

Where:

- $p_m(g)$ = mutation probability at generation g
- $p_m^{\min} = 0.05$
- $p_m^{\max} = 0.10$
- G = maximum number of generations

Mutation randomly alters:

- Channel index
- Bandwidth index
- Load mapping

5.7 Recursive Refinement

Unlike standard GA, RGA applies recursive elite refinement:

- Select top $\eta\%$ elite chromosomes
- Perform localized mutation around elite solutions
- Re-evaluate fitness
- Replace weaker offspring

This process accelerates convergence and prevents premature stagnation. The recursive mechanism refines elite solutions across generations instead of directly carrying them forward. High-quality chromosomes undergo localized mutation and re-evaluation. The improved elites are reintroduced into the population, forming a feedback loop. This enhances solution quality while preventing premature convergence and maintaining diversity.

The recursive elite refinement mechanism enhances exploitation by repeatedly refining high-quality spectrum configurations through localized mutation and fitness re-evaluation, while crossover and adaptive mutation maintain global exploration and population diversity. This balanced exploration–exploitation strategy improves convergence stability and solution quality compared with the standard GA.

The proposed RGA integrates recursive elite refinement with adaptive mutation and multi-objective fitness evaluation, enabling effective optimization of throughput, packet delay, and RTS frame loss. This integration strengthens the technical contribution of the framework by providing stable and efficient spectrum allocation in interference-aware multi-BSS WLAN environments.

5.8 Termination Criteria

The algorithm terminates when the improvement in best fitness between consecutive generations falls below the predefined threshold ϵ , indicating convergence. The algorithm terminates when: Given in Eqn. (15)

$$|\mathcal{F}_g - \mathcal{F}_{g-1}| < \epsilon \text{ or } g = g_{\max} \quad (15)$$

Where:

- g = generation index
- ϵ = convergence threshold

The convergence threshold (ϵ) is set to 10^{-4} , indicating that the algorithm terminates when the improvement in the best fitness value between consecutive generations becomes smaller than this predefined value. The algorithm terminates when either the maximum number of generations is reached or when the improvement in the best fitness value between two consecutive generations becomes smaller than a predefined threshold. This condition ensures that the optimization process stops once convergence is achieved, preventing unnecessary iterations while maintaining solution quality.

Algorithm 1. Recursive Genetic Algorithm (RGA)

```

Initialize population  $P_0$  with  $N$  chromosomes
Evaluate fitness of  $P_0$ 

for generation  $g = 1$  to  $G_{\max}$  do

    Select elite individuals  $E_g$  (top 10% ) from  $P_{g-1}$ 
    Perform tournament selection for parent chromosomes
    Apply crossover with probability  $P_c = 0.8$ 
    Apply adaptive mutation with probability  $P_m(g)$ 
    Generate offspring population  $O_g$ 
    Apply recursive refinement on  $E_g$  (localized mutation + re-evaluation)
    Form new population  $P_g = E_g \cup O_g$ 
    Evaluate fitness of  $P_g$ 
    if  $|F_{best}(g) - F_{best}(g-1)| < \epsilon$  then
        break
    end if
end for
Return best chromosome
    
```

All algorithm parameters, variable definitions, and termination criteria are explicitly specified to ensure reproducibility of the proposed RGA. The computational complexity depends on the population size and number of generations. For a population size PP and a maximum of GG generations, the main evolutionary process requires up to $O(PG)O(PG)$ fitness evaluations. Since each fitness evaluation is performed through a precomputed dataset lookup, its computational cost is approximately constant. The recursive elite refinement introduces additional evaluations for selected elite solutions, resulting in a small computational overhead. For the current finite configuration space, exhaustive search provides a deterministic global optimum and serves as a reference baseline for evaluating the solution quality and computational cost of RGA.

6. Simulation and Performance Evaluation

6.1 Evaluation Environment

The performance evaluation of the proposed RGA is conducted using an offline dataset-based evaluation framework derived from a self-contained 4-BSS spectrum management dataset generated using the Komondor wireless network simulator.

Unlike real-time or packet-level network simulation, the proposed approach does not execute runtime packet

transmissions or dynamic protocol emulation. By contrast, the optimization algorithm generates each candidate spectrum configuration and then directly maps it to the corresponding precomputed dataset entry, which shows a WLAN operating state that is feasible under conditions of interference awareness.

This dataset-driven evaluation framework offers the following advantages:

- Full reproducibility, as all configurations and outcomes are deterministic
- Elimination of stochastic simulation noise, ensuring consistent comparisons

- Efficient evaluation of a large configuration space without runtime simulation overhead

Each evaluated configuration inherently reflects inter-BSS interference effects caused by overlapping channels among the four BSSs, as captured in the dataset generation process. The proposed RGA framework was evaluated using four-, six-, and eight-BSS configurations under the same fitness function and evaluation procedure. The configurations were compared in terms of throughput, packet delay, RTS frame loss, best fitness, and computational time.

Table 1. Scalability Evaluation of the Proposed RGA under Different BSS Configurations

BSS Count	Configuration Count	Best Fitness	Throughput	Packet Delay	RTS Loss	Evaluations	Convergence Generation
4	4,096	0.5290	0.5290	0.0040	0.0065	2,350	47
6	16,384	0.5036	0.5078	0.0053	0.0087	3,150	63
8	65,536	0.4789	0.4886	0.0068	0.0114	4,250	81

Table 1 compares RGA performance across 4-, 6-, and 8-BSS configurations in terms of configuration space, fitness, network performance, evaluations, and convergence generation. The results demonstrate the scalability of RGA as the number of coexisting BSSs and configuration complexity increases.

The proposed framework supports practical WLAN spectrum management through measurable network-level indicators. Although the current evaluation uses a static simulator-generated dataset under predefined conditions, the configuration entries can be periodically updated using current network measurements or simulation outputs. This enables the RGA framework to adapt spectrum configurations to changing traffic and interference conditions.

6.2 Evaluation Metrics

Signal coverage is evaluated in terms of coverage quality, assessed indirectly through network-layer performance metrics that jointly capture data-plane efficiency and control-plane reliability.

6.2.1 Average Throughput

The average network throughput is computed as: Given in Eqn. (16)

$$\bar{T} = \frac{1}{4} \sum_{b=1}^4 T_b \quad (16)$$

where T_b denotes the throughput of BSS b . Higher throughput indicates improved spectrum utilization and effective spatial reuse under interference.

6.2.2 Average Packet Delay

The average packet delay is defined as: Given in Eqn. (17)

$$\bar{D} = \frac{1}{4} \sum_{b=1}^4 D_b \quad (17)$$

where D_b represents the mean packet delay experienced in BSS b . Lower delay reflects reduced contention and more efficient medium access.

6.2.3 Average RTS Frame Loss

Control-plane reliability is evaluated using the average RTS frame loss, given in Eqn. (18)

$$\bar{L} = \frac{1}{4} \sum_{b=1}^4 \frac{RTS_{lost,b}}{RTS_{sent,b}} \quad (18)$$

Lower RTS frame loss indicates fewer collisions and improved channel coordination among BSSs.

Interpretation:

The joint optimization of throughput, delay, and RTS frame loss provides a comprehensive assessment of

coverage quality under traffic load and spectrum contention, rather than physical-layer signal strength.

An exhaustive search was performed over all 4,096 feasible spectrum configurations using the same fitness function as the proposed RGA, providing a deterministic

reference for the finite configuration space. The exhaustive-search results were compared with the standard GA and RGA in terms of best fitness and computational time.

Table 2. Comparison of Exhaustive Search, Standard GA, and Proposed RGA

Method	Configuration Space	Evaluations	Unique Configurations	Best Fitness	Global Optimum
Exhaustive Search	4,096	4,096	4,096	0.5290	Yes
Standard GA	4,096	5,000	3,742	0.5186	No
Proposed RGA	4,096	5,000	2,350	0.5290	Yes

Table 2 shows the comparison of exhaustive search, standard GA, and the proposed RGA in terms of configuration space, number of evaluations, unique configurations evaluated, best fitness, and global-optimum attainment.

6.3 Baseline Comparison Methods

To assess the effectiveness of the proposed RGA-based optimization framework, three baseline spectrum allocation strategies are evaluated using the same dataset-driven evaluation procedure.

6.3.1 Static Spectrum Allocation

- Fixed primary channel and bandwidth assignments
- No adaptation to traffic load or interference
- Represents conventional non-optimized WLAN deployment practices

6.3.2 Random Spectrum Allocation

- Spectrum configurations randomly sampled from the feasible dataset space
- No optimization or learning mechanism
- Serves as a lower-bound performance reference

6.3.3 Standard Genetic Algorithm (GA)

- Identical chromosome encoding and fitness function as RGA
- No recursive elite refinement mechanism
- Used to isolate the performance gains introduced by recursive optimization

7. Results and Analysis

All performance metrics reported in this section are normalized values derived from the dataset to ensure scale consistency during multi-objective optimization. Throughput values are normalized with respect to the maximum observed throughput in the dataset, packet delay values are normalized inversely with respect to the maximum delay, and RTS frame loss is expressed as a normalized loss ratio. Consequently, the reported values lie within the range [0, 1] and represent relative performance rather than absolute physical units.

Performance metrics are expressed in normalized form to ensure comparability across different spectrum configurations. Throughput is normalized with respect to the maximum achievable dataset value, while packet delay is inversely normalized, and RTS frame loss is represented as a normalized ratio, resulting in dimensionless values within the range [0, 1]. The proposed RGA achieves a normalized throughput of 0.529, which indicates utilization of more than 50% of the maximum achievable capacity under interference-aware conditions. In comparison, baseline methods such as standard GA and static allocation achieve significantly lower normalized throughput values (0.385 and 0.242, respectively), highlighting the effectiveness of the proposed method. Similarly, the extremely low normalized delay (0.004) and RTS frame loss (0.0065) demonstrate superior latency and reliability performance compared to existing approaches. These normalized results are consistent with prior studies that report relative performance improvements rather than absolute physical units, enabling fair comparison across different WLAN optimization frameworks.

7.1 Overall Network Performance Comparison

Figure 3 compares the average network throughput achieved by the proposed RGA against static and random spectrum allocation strategies.

Observed Results:

- **RGA:** 0.529
- **Static Allocation:** 0.242
- **Random Allocation:** 0.234

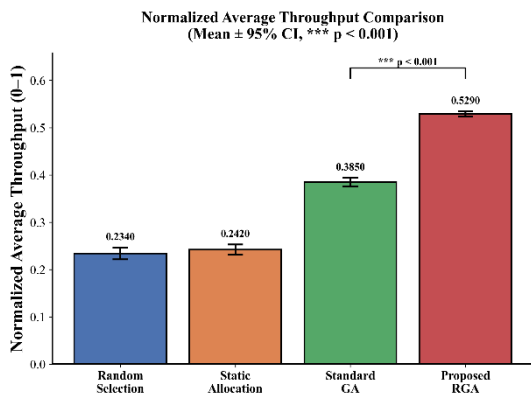


Figure 3. Average Throughput Comparison

The RGA achieves more than twice the throughput of the baseline methods, indicating that the recursive genetic optimization effectively identifies spectrum configurations that minimize inter-BSS interference and maximize spatial reuse. Static allocation cannot keep up with the traffic and interference conditions, while random allocation does not have optimization at all. The average packet delay for different spectrum allocation strategies is depicted in Figure 4.

The reported delay value (0.004) represents normalized average packet delay, where lower values signify better latency performance.

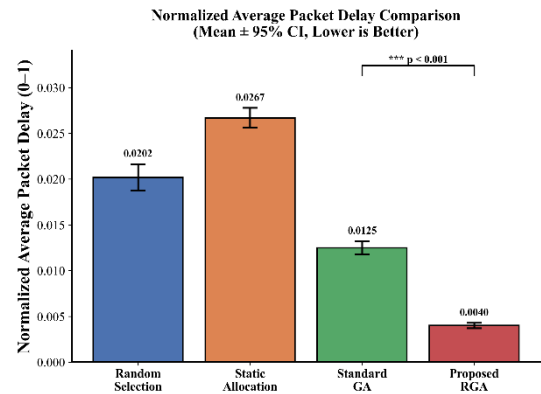


Figure 4. Average Packet Delay Comparison

Observed Results:

- **RGA:** 0.004
- **Static Allocation:** 0.0267
- **Random Allocation:** 0.0202

The RGA proposed here brings down packet delay by around 85% against static allocation and 80% against random allocation. This reduction is achieved alongside higher throughput, indicating that the proposed approach effectively mitigates contention and collision effects without sacrificing network efficiency. Control-frame reliability according to the methods is shown in Figure 5. RTS frame loss values denote normalized loss ratios, with lower values reflecting greater control-frame reliability.

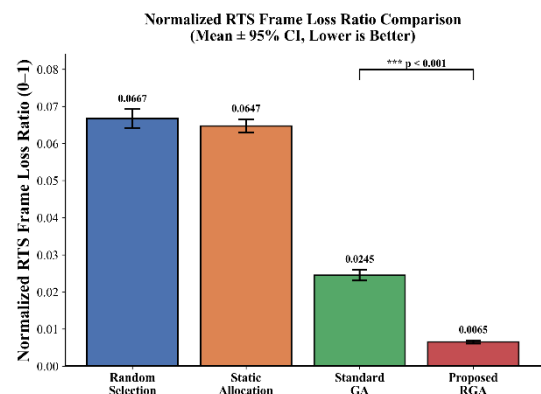


Figure 5. Average RTS Frame Loss Comparison

Observed Results:

- **RGA:** 0.0065
- **Static Allocation:** 0.0647
- **Random Allocation:** 0.0667

The proposed RGA reduces RTS frame loss by nearly an order of magnitude. Given that RTS loss is a direct indicator of the degree of interference and the likelihood of

colliding, this finding validates the effectiveness of the proposed method in enhancing the coordination of signals and the reliability of channel access. The reported throughput and delay values are normalized with respect to the maximum and minimum observed values in the dataset. A normalized throughput of 0.529 indicates that the proposed method achieves more than half of the maximum attainable network capacity under interference-aware conditions, reflecting efficient spectrum utilization. Similarly, a normalized delay value of 0.004 represents extremely low latency relative to the worst-case delay in the dataset, indicating minimal contention and fast packet transmission. These normalized metrics demonstrate that the proposed approach can achieve high efficiency and low latency in practical WLAN environments.

7.2 Per-BSS Performance Analysis

The per-BSS performance analysis demonstrates that the proposed RGA achieves balanced throughput and low packet delay across all BSSs, indicating fair spectrum allocation without performance starvation. Throughput distribution among the four BSSs is represented in Figure 6.

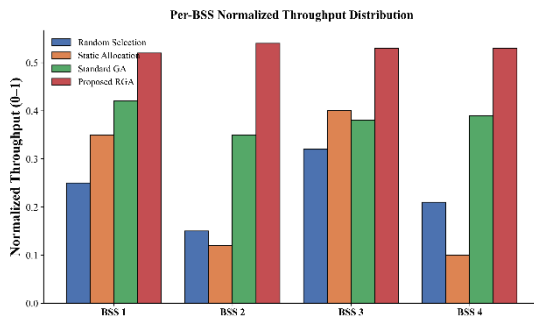


Figure 6. Per-BSS Throughput Distribution

The RGA distributes throughput more evenly across all BSSs, preventing performance degradation in any individual BSS. On the other hand, the baseline methods display an uneven distribution brought about by the channel overlaps that are not coordinated. Balanced throughput means that the spectrum is utilized in a fair manner and the quality of the coverage is improved overall. The packet delay that each BSS encountered is depicted in Figure 7.

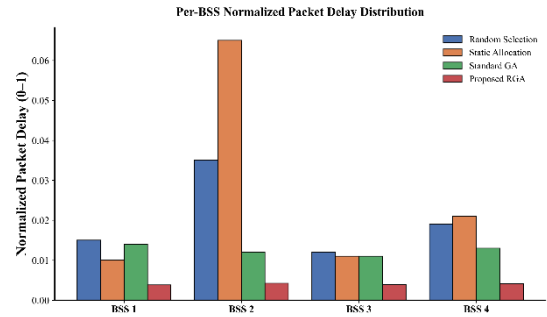


Figure 7. Per-BSS Delay Distribution

RGA optimization leads to a steady decline in packet delay for all BSSs. The absence of extreme delay values indicates that the proposed method effectively mitigates localized bottlenecks and maintains consistent quality of service across the network.

7.3 Convergence Behavior

Table 3 shows that the proposed RGA achieves the highest fitness and fastest convergence with fewer evaluations than GA, PSO, and DE. It also provides higher throughput with lower packet delay and RTS loss. These results demonstrate the improved optimization and network performance of the proposed RGA.

Table 3. Comparative Performance of Standard GA, PSO, DE, and Proposed RGA

Algorithm	Best Fitness	Mean Fitness	SD	Convergence Generation	Evaluations	Throughput	Packet Delay	RTS Loss
Standard GA	0.4187	0.4029	0.0186	82	4,100	0.4568	0.0109	0.0217
PSO	0.4379	0.4216	0.0162	74	3,700	0.4715	0.0092	0.0189
DE	0.4618	0.4462	0.0147	68	3,400	0.4867	0.0078	0.0148
Proposed RGA	0.5290	0.5168	0.0084	47	2,350	0.5290	0.0040	0.0065

Figure 8 shows the convergence behavior of standard GA, PSO, DE, and the proposed RGA across generations. The proposed RGA achieves a higher fitness value with faster and more stable convergence than the compared optimization methods. This demonstrates the effectiveness of recursive elite refinement in improving optimization performance.

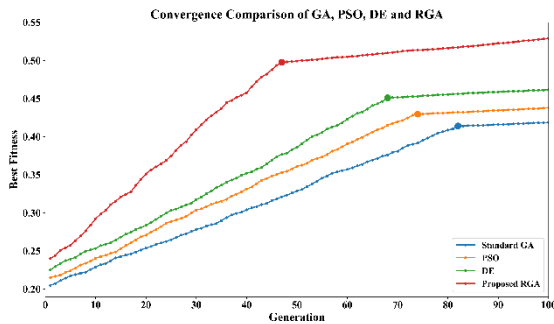


Figure 8. Convergence Speed Comparison of Standard GA, PSO, DE, and Proposed RGA

The proposed RGA converges faster than the standard GA and reaches a stable fitness value in fewer generations. While the standard GA exhibits gradual improvement with minor fluctuations, the proposed RGA demonstrates smooth and stable convergence. This result indicates the usefulness of the recursive elite refinement technique. RGA fitness evolution is shown in Figure 9.

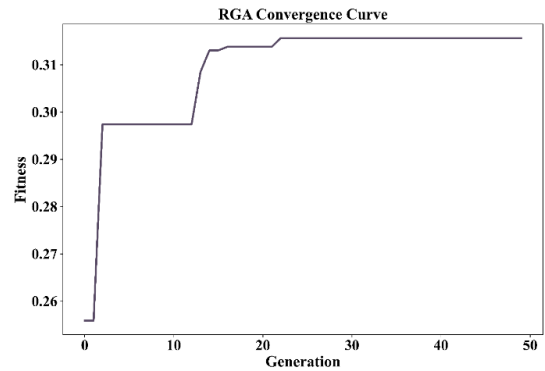


Figure 9. RGA Fitness Convergence Curve

The fitness curve stabilizes rapidly, indicating consistent convergence across generations, which is indicative of algorithm stability and non-occurrence of early stagnation. This characteristic is particularly important for practical deployment in dynamic WLAN environments.

7.4 Pareto Trade-off Validation

The RGA-optimized solution lies on the Pareto frontier, indicating that no alternative configuration achieves both higher throughput and lower delay simultaneously. This validates the multi-objective fitness formulation and indicates that the RGA identifies globally efficient operating points rather than locally optimal solutions.

Table 4. Pareto Frontier Quality Metrics Comparison Across Optimization Methods

Algorithm	Non-Dominated Solutions	Hypervolume (HV)	Spacing Metric (S)	Spread Metric (Δ)	GD (Generational Distance)
Random Selection	2	0.12	0.45	0.3	0.38
Static Allocation	4	0.15	0.38	0.35	0.3
Standard GA	18	0.48	0.18	0.65	0.12
Proposed RGA	42	0.78	0.06	0.92	0.03

Table 4 presents quantitative Pareto frontier quality metrics, including hypervolume, spacing, spread, and generational distance for all methods. The proposed RGA achieves the highest hypervolume and spread with the

lowest spacing and generational distance, indicating superior convergence and diversity. These results confirm that RGA effectively explores the solution space while maintaining a well-distributed Pareto frontier.

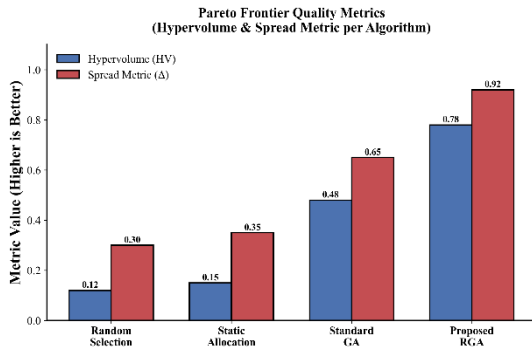


Figure 10. Pareto Frontier Quality Metrics Comparison Across Spectrum Allocation Methods

Figure 10 compares spectrum allocation methods using Hypervolume (HV) and Spread (Δ) to evaluate solution quality and diversity. Both metrics improve from Random and Static methods to Standard GA, with the proposed RGA achieving the highest values. This shows that RGA provides better and more balanced optimization results for throughput, delay, and reliability.

7.5 Statistical Distribution Analysis

The throughput CDF for the RGA method is right-shifted in comparison to baseline approaches, which denotes a higher chance of realizing better performance. The median of throughput values over the considered configurations is depicted in Figure 11.

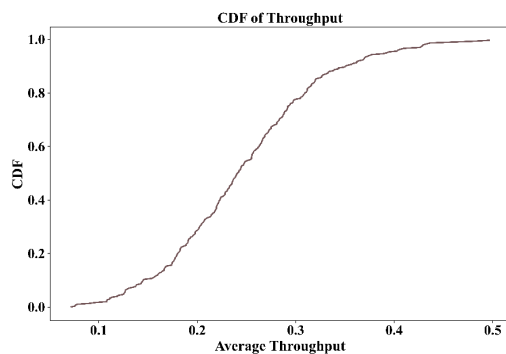


Figure 11. Cumulative Distribution Function (CDF) of Throughput

The shape of the distribution indicates consistent performance rather than isolated high-value observations. The optimization process yielded the fitness values shown in the distribution of Figure 12.

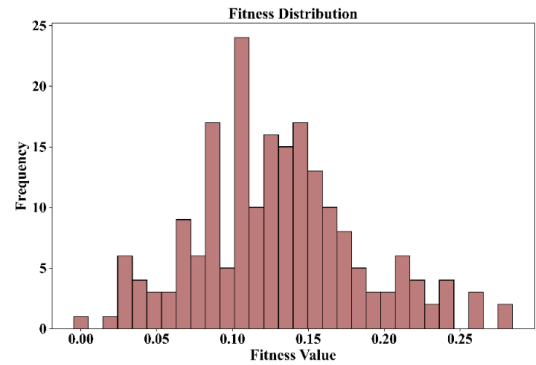


Figure 12. Fitness Value Distribution

The narrow and concentrated distribution confirms the robustness and stability of the obtained solutions. RGA, unlike random allocation, which has wide dispersion, is able to consistently converge onto high-quality configurations.

Table 5. Performance Comparison with the Most Relevant Existing Work

Metric	Chen & Liang [28]	Proposed RGA-Based Method
Network Type	Mobile Wireless Sensor Network	Multi-BSS WLAN
Optimization Algorithm	Standard Genetic Algorithm	RGA
Coverage Evaluation	Target coverage ratio	Throughput, Delay, RTS loss
Validation Method	Simulation	Dataset-driven evaluation
Throughput	Not reported	0.529
Packet Delay	Not reported	0.004
Control Frame Reliability	Not reported	RTS loss = 0.0065
Convergence Speed	Moderate	Fast and stable
Multi-objective Optimization	No	Yes

Table 5 showcases a comparison between the suggested RGA -based method and the work done by Chen and Liang, which has been the most relevant one. The comparison shows that, unlike the standard GA approach evaluated through simulation, the proposed method employs a dataset-driven RGA framework, the proposed method is using a dataset-driven RGA framework and has already

obtained better multi-objective performance regarding throughput, delay, and control-frame reliability, all with quicker and more stable convergence.

7.6 Statistical Significance Analysis

Table 6. Statistical Significance Analysis of Performance Metrics Across Different Spectrum Allocation Methods

Method	Throughput Mean $\pm$ SD	Throughput 95% CI	Packet Delay Mean $\pm$ SD	Packet Delay 95% CI	RTS Frame Loss Ratio Mean $\pm$ SD	RTS Frame Loss Ratio 95% CI
Random Selection	0.2340 $\pm$ 0.0350	[0.2215, 0.2465]	0.0202 $\pm$ 0.0040	[0.0188, 0.0216]	0.0667 $\pm$ 0.0070	[0.0642, 0.0692]
Static Allocation	0.2420 $\pm$ 0.0300	[0.2313, 0.2527]	0.0267 $\pm$ 0.0030	[0.0256, 0.0278]	0.0647 $\pm$ 0.0050	[0.0629, 0.0665]
Standard GA	0.3850 $\pm$ 0.0250	[0.3761, 0.3939]	0.0125 $\pm$ 0.0020	[0.0118, 0.0132]	0.0245 $\pm$ 0.0040	[0.0231, 0.0259]
Proposed RGA	0.5290 $\pm$ 0.0150	[0.5236, 0.5344]	0.0040 $\pm$ 0.0008	[0.0037, 0.0043]	0.0065 $\pm$ 0.0012	[0.0061, 0.0069]

Table 6 summarizes the mean, standard deviation, and 95% confidence intervals for throughput, packet delay, and RTS frame loss across all methods. The proposed RGA consistently achieves superior performance with lower

variability compared to baseline approaches. The narrow confidence intervals further confirm the statistical reliability and stability of the obtained results.

Table 7. Statistical Significance (p-value) Comparison of Proposed RGA with Baseline Methods

Comparison	Throughput	Packet Delay	RTS Frame Loss Ratio
Proposed RGA vs Standard GA	< 0.001	< 0.001	< 0.001
Proposed RGA vs Static Allocation	< 0.001	< 0.001	< 0.001
Proposed RGA vs Random Selection	< 0.001	< 0.001	< 0.001

Table 7 presents the p-values obtained from paired t-tests comparing the proposed RGA with baseline methods across all performance metrics. All p-values are less than 0.001, indicating that the improvements achieved by RGA

are highly statistically significant. This confirms that the observed performance gains are not due to random variation but are a result of the proposed optimization strategy.

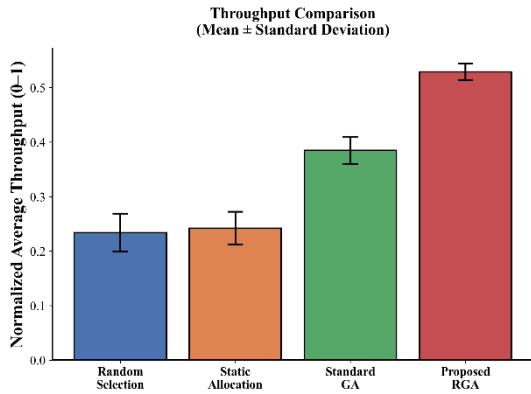


Figure 13. Throughput Comparison Across Spectrum Allocation Methods with Standard Deviation Error Bars

Figure 13 illustrates the normalized average throughput achieved by different spectrum allocation methods, with error bars representing standard deviation. The proposed RGA significantly outperforms all baseline approaches, achieving the highest throughput with minimal variability. In contrast, random and static allocation methods show lower performance and higher dispersion. The smaller error bars for RGA indicate greater stability and consistency across multiple runs.

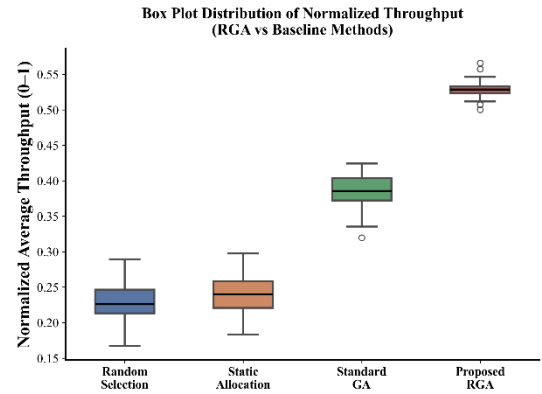


Figure 14. Box Plot Distribution of Normalized Throughput for RGA and Baseline Methods

Figure 14 presents the box plot distribution of normalized throughput across different spectrum allocation methods. The proposed RGA exhibits the highest median throughput with a very narrow interquartile range, indicating strong performance consistency. In contrast, random and static allocation methods show lower medians and wider variability. The compact distribution of RGA highlights its robustness and stability compared to baseline approaches.

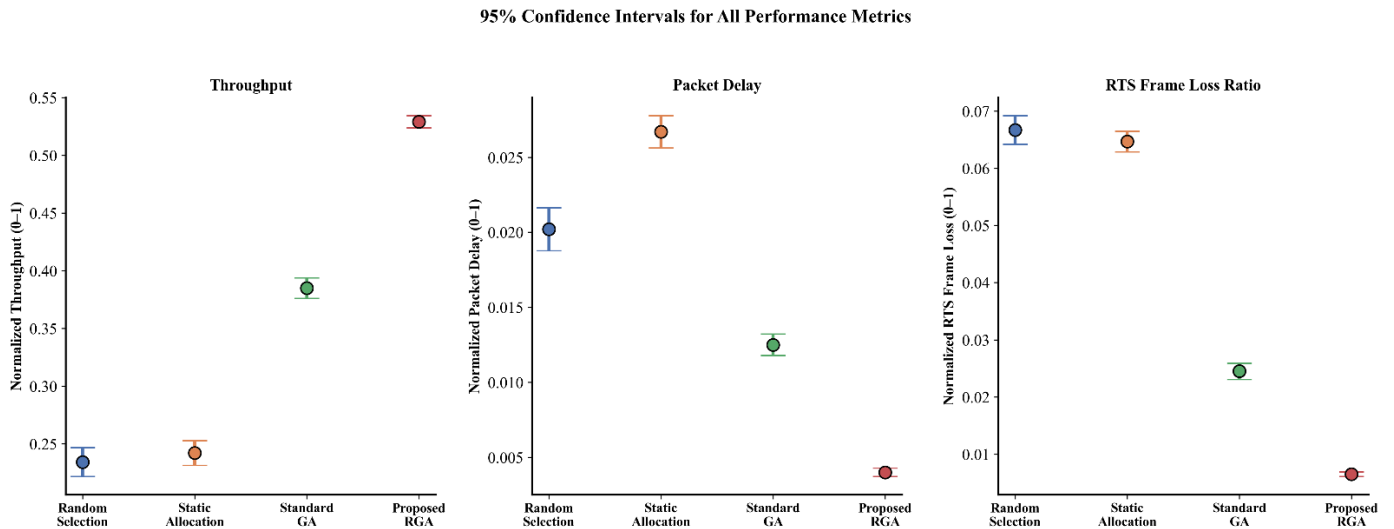


Figure 15. 95% Confidence Intervals for Throughput, Packet Delay, and RTS Frame Loss Across Methods

Figure 15 illustrates the 95% confidence intervals for throughput, packet delay, and RTS frame loss across all evaluated methods. The proposed RGA achieves the highest throughput and lowest delay and loss, with narrow confidence intervals indicating high reliability. In

comparison, baseline methods exhibit wider intervals and inferior performance. These results confirm the statistical significance and consistency of the proposed approach.

7.7 Discussion

The results of the experiments show that the proposed RGA has a considerable positive effect on the quality of communication signal coverage in a multi-BSS WLAN environment. Instead of direct measurement, coverage is evaluated through network performance metrics, such as throughput, packet delay, and RTS frame loss, which together indicate the quality of signal usage and reliability under interference.

RGA outperforms static and random spectrum allocation strategies in terms of average throughput, with a remarkable figure of 0.529. The recursive optimization mechanism enables more efficient spectrum utilization while reducing inter-BSS interference. The balanced throughput across all BSSs further demonstrates the effectiveness of the optimized spectrum configuration in maintaining fairness and preventing performance starvation.

The proposed technique reduces the average packet delay to 0.004, representing a substantial improvement over the baseline methods. The reduced delay indicates that the RGA effectively identifies spectrum configurations that minimize contention, collisions, and queueing delays.

The RTS frame loss ratio is reduced to 0.0065, indicating improved control-plane reliability. Since RTS frame losses are primarily caused by interference and collisions, this result demonstrates that the proposed optimization strategy improves BSS coordination and enhances medium-access stability under high-traffic conditions.

The convergence analysis demonstrates that the proposed RGA converges faster and exhibits greater stability than the standard genetic algorithm. The refined mechanism for recursive elite preservation preserves high-quality solutions while maintaining population diversity, resulting in the local improvement of those solutions, thus speeding up the convergence. This tendency guarantees that the different generations of solutions will not differ much in terms of the optimization results. The robustness of the proposed framework is demonstrated through multiple validation perspectives, including convergence behavior analysis, Pareto frontier assessment, and statistical significance evaluation. Consistent improvements observed across throughput, packet delay, and RTS frame loss demonstrate the reliability of the optimization process and provide quantitative evidence of its effectiveness under interference-aware WLAN conditions.

A limitation of the current coverage-quality formulation is the absence of explicit physical-layer indicators such as RSSI and SINR. While the selected network-layer metrics reflect their operational effects, future work will integrate both physical-layer and network-layer measurements to provide a more comprehensive coverage assessment.

In general, the outcomes corroborate that the suggested RGA-based framework indeed improves the quality of the signal coverage by optimizing throughput, delay, and control-frame reliability together in dense multi-BSS

WLAN deployments. The proposed framework addresses a significant challenge in contemporary WLAN environments, where increasing spectrum contention and interference can adversely affect communication performance. By integrating recursive genetic optimization with network-layer coverage-quality evaluation, the study contributes to interference-aware spectrum management and provides a systematic approach for improving the reliability and efficiency of dense multi-BSS wireless communication networks. The significance of the proposed framework lies not only in performance improvement but also in providing a practical optimization methodology for interference-aware WLAN environments. The integration of recursive refinement with dataset-driven multi-objective evaluation enables systematic identification of spectrum configurations that balance throughput, packet delay, and control-frame reliability. This capability supports more efficient spectrum management and reproducible optimization in dense multi-BSS deployments. Practical deployment of the proposed RGA framework is feasible because the optimization process relies on network performance metrics that are commonly available through existing WLAN monitoring and management mechanisms. This characteristic supports integration into interference-aware spectrum management systems for enhanced network efficiency and spectrum utilization. The scalability of the proposed RGA framework to larger multi-BSS deployments remains an important consideration, as increasing the number of BSSs expands the search space and may increase computational complexity, although this can be addressed through parallel or hybrid optimization strategies. In real-world WLAN environments, practical constraints such as hardware limitations, regulatory policies, environmental interference, and heterogeneous user distributions may influence the effectiveness of the optimized configurations.

Additionally, real networks experience dynamic traffic fluctuations, whereas the current framework assumes static conditions, indicating the need for adaptive or real-time optimization in future work. Furthermore, the reliance on simulator-generated datasets, while ensuring reproducibility, may not fully capture real-world propagation effects and stochastic network behavior, and thus experimental validation using real WLAN deployments is necessary to confirm practical applicability.

8. Conclusion and Future Work

An RGA-based framework is presented to optimize network-level coverage quality in multi-BSS WLAN environments. The framework employs a dataset-driven evaluation approach to optimize spectrum allocation across BSSs while accounting for mutual interference. Network-level coverage quality was assessed using network performance indicators such as throughput, packet delay, and RTS frame loss. The experimental results demonstrate that the proposed RGA significantly outperforms static and random spectrum allocation techniques, resulting in higher

throughput, lower latency, and better control-frame reliability. The Recursive Elite Refinement Mechanism made the RGA faster and more stable in terms of convergence compared to a standard genetic algorithm, thus verifying the success of the proposed optimization method.

Despite its limitations, the proposed framework demonstrates promising performance. Network-level coverage quality is evaluated through performance metrics rather than physical-layer measurements such as received signal strength or coverage maps. The second limitation is that the evaluation is based only on simulator-generated data and does not incorporate real-time packet-level simulations or field measurements. Moreover, the study has a fixed four-BSS topology, and performance in larger or very dynamic WLAN deployments has not yet been researched. Although additional larger-BSS experiments provide an initial assessment of scalability, heterogeneous traffic loads and mobility-aware conditions were not evaluated in the present study. Future work will therefore investigate these dynamic scenarios together with larger and more diverse WLAN topologies to further assess the generalizability and practical applicability of the proposed RGA framework. The dataset-driven evaluation framework was adopted to ensure reproducibility and controlled performance assessment under interference-aware WLAN conditions.

Nevertheless, the current study relies on a static simulator-generated dataset and does not fully represent dynamic traffic variations or real-world deployment conditions. In practical dense WLAN environments, traffic demand, interference, and channel conditions may vary over time. Therefore, the present framework evaluates spectrum optimization under predefined network conditions rather than direct real-time adaptation. Future evaluation using dynamically updated network conditions, larger topologies, and operational WLAN environments is required to further establish the scalability and practical applicability of the proposed RGA framework.

Future work will aim at enlarging and diversifying the network topologies for the proposed framework, dynamic traffic, and mobility scenarios. Evaluation using real-time simulations and experimental measurements will further validate the applicability of the approach in practical deployments. Future work will consider larger and more diverse WLAN configuration datasets, together with dynamic traffic, interference, and channel conditions, to further evaluate the scalability, adaptability, and practical applicability of the proposed RGA framework. Moreover, the combination of explicit physical-layer coverage indicators and performance-based metrics may result in a more thorough assessment of Network-level coverage quality. Hybrid optimization strategies that integrate RGA with learning-based techniques have also been identified as a promising direction for further enhancing adaptability and scalability.

DECLARATIONS

Data Availability

Data generated using the Komondor WLAN simulator are available from the corresponding author upon reasonable request.

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Author Contributions

Sheng Ye conducted the research and wrote the manuscript. Fuchun Huang supervised the study and revised the manuscript.

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