TELKOMNIKA Telecommunication, Computing, Electronics and Control
Vol. 24, No. 5, October 2026, pp. 1457∼1468
ISSN: 1693-6930, DOI: 10.12928/TELKOMNIKA.v24i5.27024

Power optimization in 5G network bands using modified genetic algorithm

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Article Info

Article history:

Received Feb 25, 2026
Revised Jun 3, 2026
Accepted Jun 30, 2026

Keywords:

Genetic algorithm
Heterogeneous networks
Interference cancellation
Machine learning optimization
Next generation wireless networks
Power optimization

ABSTRACT

This study investigates power optimization techniques in fifth-generation (5G) networks to enhance network performance across multiple metrics. Slow convergence and often getting stuck in local optima is an issue in traditional genetic algorithm (GA). Whereas, with machine learning (ML) algorithms large datasets are required and constraints cannot be enforced. To avoid local minima and achieve global optimal solution, the average fitness value is checked in modified GA after completion of the total count N_c, so that the change in fitness should be greater than 1%. In this research work, modified GA algorithm is used to optimize power allocation, minimize interference, and improve resource management across different frequency bands, specifically 700 and 3500 MHz. The results show that the modified GA achieves enhancement in spectral efficiency by 4% and 18%, success probability by 16% and 13% and power efficiency by 30% and 28% at 700 MHz and 3500 MHz frequencies respectively over ML at signal-to-interference-plus-noise ratio (SINR) = 30 dB. The analysis of power consumption with respect to threshold SINR reveals that modified GA approach reduces power usage by 18% and 14% over ML at 700 and 3500 MHz respectively, while maintaining acceptable SINR levels, especially at higher thresholds.

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1. INTRODUCTION

As fifth-generation (5G) networks continue to emerge, the need for high-capacity, dependable, and energy-efficient communication infrastructures has become increasingly critical. The deployment of 5G represents a transformative step in wireless technology, significantly strengthening connectivity across multiple sectors. The spectrum bands of 700 and 3500 MHz are central to the development of these networks. The 700 MHz band is really good for covering areas and avoiding physical obstacles, which makes it perfect for use in suburban and rural areas [1]. On the other hand, the 3500 MHz band is great for handling a lot of users and heavy internet traffic in cities [2]. By combining these frequency resources, the overall performance of system can be improved [3].

As 5G networks [4] continue to grow, people are now focusing on making them energy efficient. This is important to reduce costs and ensure that services are reliable in places such as smart cities that need a lot of energy. The 700 MHz and 3500 MHz spectrum bands play a role, in this as they help to support the expansion of 5G ecosystems [5], [6]. The new energy-saving methods do not only lower the carbon footprints of the 5G network. They also help the 5G network work well for a long time [7]. At the time the smart traffic management solutions make sure that the quality of the 5G network service is good even when the 5G network is very busy [8]. In short using the 700 MHz and 3500 MHz frequency bands for the 5G network along with the energy-optimization strategies shows that the 5G network can provide high-performance and sustainable wireless connectivity [9], [10]. These advancements do not just give the 5G network data rates but they also provide a foundation for the communication systems of the future that can adapt to the complex needs of a society that is becoming increasingly digital.

Many methods have been tried to manage energy. It is still a challenge to optimize energy in such a complex environment. The traditional machine learning (ML) methods need a lot of training data and it may not work well under new traffic conditions. On the hand the evolutionary algorithms, especially the genetic algorithms (GA) provide a flexible and data-independent way to solve complex optimization problems. The GA are well-suited to handle the trade-offs between minimizing power consumption and maintaining the quality of the 5G network service. A GA approach for 5G power optimization that can adapt to the changing conditions converge faster avoid local optima and associate users to achieve energy efficiency without compromising the performance of the 5G network has been proposed in this research work. The 5G networks can adjust their energy consumption based on the demands of the users and the conditions of the 5G network through modulation and coding schemes. Another aspect which play an important role in improvement of capacity, coverage and also addressing energy efficiency are the cells in 5G networks [11]. When the small cells are implemented strategically the operators can reduce the distance between the users and the 5G network thus reducing the power required to transmit signals. In terms of design of the 5G network, efficient association of users is another factor in power optimization.

A survey on user association in the 5G networks provides algorithms that facilitate optimal user connectivity to base stations (BS), which is an essential process that improves both the energy performance and the overall efficiency of the 5G network. By minimizing the required transmission power through user association strategies the 5G networks can significantly enhance their sustainability footprint. Furthermore the implementation of smart grid technologies in conjunction with the 5G networks offers a way to save energy. A comprehensive review highlights how the 5G network can support grid functionalities enabling improved energy management and distribution [12]. By using real-time analysis of data and advanced communication capabilities the 5G networks can optimize energy flows between systems thereby making a substantial contribution to sustainability efforts. As the communication between machines continues to expand under the 5G network energy optimization becomes more critical.

The efficient management of data flows between devices is essential to mitigate power consumption [13]. The collaborative nature of the internet of things (IoT) ecosystems requires communication protocols that prioritize energy-saving measures further reflecting the importance of sustainable 5G network design. Nonetheless the challenges in power optimization within the 5G networks remain numerous and diverse. Research underscores the need for innovation in designing the 5G networks and devices specifically tailored for the 5G era [14]. This highlights the necessity for advancements that directly target energy consumption ensuring that energy efficiency evolves alongside increasing demands for performance and greater capacity of the 5G network.

Recent studies have introduced interference coordination strategies that are highly effective in the 5G networks. Complementing this [15] the benefits of multiple-input multiple-output (MIMO) in enhancing signal quality and mitigating interference in rural areas demonstrate the versatility of advanced technologies across different geographic contexts. The ultra-dense cell deployments have also played a role in addressing capacity and signal-to-interference-plus-noise ratio (SINR) challenges in cellular systems. Continuous research on power and delay optimization [16] applies learning to refine resource allocation in advanced 5G networks. Evaluations of novel 5G radio architectures [17] highlight the evolution of 5G network design principles while studies on energy efficiency in IoT applications reflect a broader trend, toward sustainable communication frameworks [18]. The intelligent reflecting surfaces improve 5G network access and connectivity contributing to better interference management [19].

ML and GA have become prominent approaches to addressing energy optimization challenges in 5G networks. ML leverages historical data to build predictive models for real-time power management without compromising quality of service (QoS), employing techniques such as regression, neural networks, and reinforcement learning. GA, a bio-inspired optimization algorithm, effectively explores complex and nonlinear solution spaces, excelling in multi-objective scenarios where it balances energy efficiency with performance metrics such as latency and throughput. While ML provides rapid and scalable solutions, GA offers flexibility and robustness in handling constraints and dynamic environments. This paper examines the strengths and limitations of these techniques in 5G networks and provides insights into their comparative performance across different use cases. The effective development of 5G networks necessitates innovative energy optimization techniques to enhance efficiency and reduce operational costs. Optimization methods play a crucial role in improving key performance indicators (KPIs), enabling increasing demand to be met without excessive energy consumption [20]. Multi-connectivity has been investigated as a technique for achieving ultra-reliable low-latency communication in 5G networks [21].

Advances in 5G technology further strengthen performance and connectivity, supporting efficient energy utilization while maintaining QoS [22]. Moreover, 5G networks have transformative potential in enabling intelligent and sustainable cities, underscoring the need for continuous research in power optimization to improve overall network performance and energy efficiency [23]. The rapid expansion of 5G also requires sophisticated interference management strategies due to the growing density of users and devices. GA has emerged as an effective tool for optimizing power allocation in multi-tier heterogeneous networks, where energy optimization directly improves network performance. A GA-based resource allocation scheme for device-to-device (D2D) scenarios was proposed in [24], demonstrating its ability to mitigate interference while ensuring optimal resource utilization. The study highlighted that GA can significantly enhance communication efficiency, supporting the broader design goals of 5G networks. Their findings emphasized that GA-based techniques systematically address multiple constraints, achieving substantial performance gains in real-time communication scenarios. Finally, Sharma *et al.* [25] explored optimal power allocation for downlink 5G communications by combining GA with complementary optimization strategies. Their results indicated that hybrid GA approaches not only improve energy distribution but also enhance overall network performance through more effective interference management.

2. SYSTEM MODEL

A 5G network with multiple BS and users distributed over a geographical area is considered. In Figure 1 BS are represented as BS_i. These are the network's infrastructure elements, providing wireless communication services to user equipments (UEs). Each BS has its own coverage area (depicted as circles). BSs transmit power P_i to their associated users, considering factors like path loss and interference. UE are represented as mobile devices within the coverage areas of BSs. Each UE connects to a serving BS for communication. The serving BS is typically selected based on the strongest received signal power. The channel gain decreases with distance due to path loss and other propagation effects. The green arrow represents the desired communication link between a UE and its serving BS whereas the red arrows shows interference from neighboring BSs, which negatively affects the SINR. The orange arrow shows the interference between UE to UE. The key metric for determining the quality in 5G Network depends on: (i) signal strength from the serving BS, (ii) interference from other BSs, and (iii) noise power in the network. Improving SINR is crucial for achieving higher data rates and better user experience. Each BS transmits at a power level P_i, which can be optimized (e.g., using algorithms like GA to minimize interference and maximize network efficiency. Table 1 presents the nomenclature of the symbols that has been used throughout the paper.

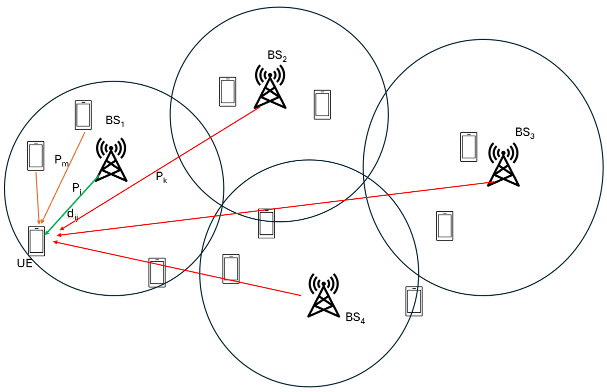


Figure 1. System model for 5G network

Table 1. Nomenclature of symbols

Symbol	Description	Unit
P_j	Transmit power of the serving BS j for user i	W
h_{ij}	Channel gain between BS j and user i (distance, path loss, fading)	–
P_k	Transmit power of interfering BS k	W
h_{ik}	Channel gain between interfering BS k and user i	–
P_m	Transmit power of interfering UE m	W
h_{im}	Channel gain between interfering user m and user i	–
N_0	Thermal noise power	W or dBm
k_B	Boltzmann constant	1.38×10^{-23} J/K
T	System temperature	K
B	System bandwidth	Hz
d_{ij}	Distance between BS j and user i	m
d_{im}	Distance between interfering user m and user i	m
g_{ij}	Channel fading coefficient between BS j and user i	–
P_{CU_i}	Power allocated to the ith cellular user	W
F_i	Fitness function	–
N	Size of a population	–

2.1. SINR calculation

The SINR for user i connected to a BS j in a 5G network can be expressed as:

$$\text{SINR}_i = \frac{P_j\, h_{ij}}{\sum\limits_{k \neq j} P_k h_{ik} + \sum\limits_{\substack{m \in U \\ m \neq i}} P_m h_{im} + N_0}, \tag{1}$$

$$N_0 = k_B\, T\, B, \tag{2}$$

2.2. Mathematical model for power optimization objective

The goal of power optimization is to maximize SINR while satisfying constraints on power, interference, and fairness of the user.

$$Objective function: \quad \min \sum_i P_i \tag{3}$$

$$Constraints: \quad P_j \leq P_{\text{max}}, \quad \forall j, \tag{4}$$

$$\sum_{k \neq j} P_k h_{ik} \leq I_{\text{th}}, \quad \forall i, \tag{5}$$

$$\text{SINR}_i \geq \text{SINR}_T, \quad \forall i. \tag{6}$$

The SINR for user i is defined as:

$$\text{SINR}_i = \frac{P_j\, d_{ij}^{-\gamma} g_{ij}}{\sum\limits_{k \neq j} P_k d_{ik}^{-\gamma} g_{ik} + \sum\limits_{\substack{m \in U \\ m \neq i}} P_m d_{im}^{-\gamma} g_{im} + N_0}, \tag{7}$$

3. POWER OPTIMIZATION IN 5G NETWORKS USING MODIFIED GA

The main goal of the GA technique is to minimize the amount of power that is used. This is done while making sure that the signal quality is good enough, for all the users. Power is allocated in such a way that it improves the signal quality and also helps to minimize interference. Optimal power allocation enhances the SINR and supports effective interference cancellation. The downlink power allocation vector for cellular users can be represented as:

$$P_{CU} = [P_{CU_1}, P_{CU_2}, \ldots, P_{CU_n}]^T$$

where, P_{CU_n} is the power allocated to the n^{th} user. The total power consumption minimization for each cellular user is formulated as

$$min\sum_{i=1}^{n} P_{CU_i}, \tag{8}$$

$$P_{CU_i} = w_i P_{max}, \tag{9}$$

$$SINR_{CU_i} \geq SINR_T, \tag{10}$$

Here P_{CU_i} is the power transmitted by the i^{th} user and is obtained by multiplying the optimal weight w_i with the power amplification factor which is a constant. The objective is to calculate the optimal weights w_i so that when multiplied by a power amplification factor gives optimal power, such that it meets the condition. where, SINR_T is the SINR threshold at the UE. A weight-based user scheduling algorithm [20] is used for assigning users to BS.

3.1. Modified GA

A GA is an evolutionary technique designed to solve search and optimization problems. Figure 2 illustrates the working principle of a modified GA used for optimization, specifically designed to avoid local minima and guide convergence toward a global optimum. The algorithm begins by initializing the maximum number of generations (G). A uniformly distributed and independent initial population is generated to ensure diversity within the solution space. Each candidate solution within the population is represented using a binary encoding scheme, which facilitates the efficient execution of genetic operations such as crossover and mutation. The effectiveness of these solutions is then measured against the optimization objectives, for example, improving the SINR or reducing power consumption. If the fitness criteria such as a predefined threshold are satisfied, the algorithm stops and returns the current best solution. Otherwise, it proceeds to the next generation. If it reaches maximum number of iterations and the average fitness value has not changed by more than 1%, the population is reinitialized, and the process repeats. The algorithm also monitors the change in average fitness, terminating if the criteria are met.

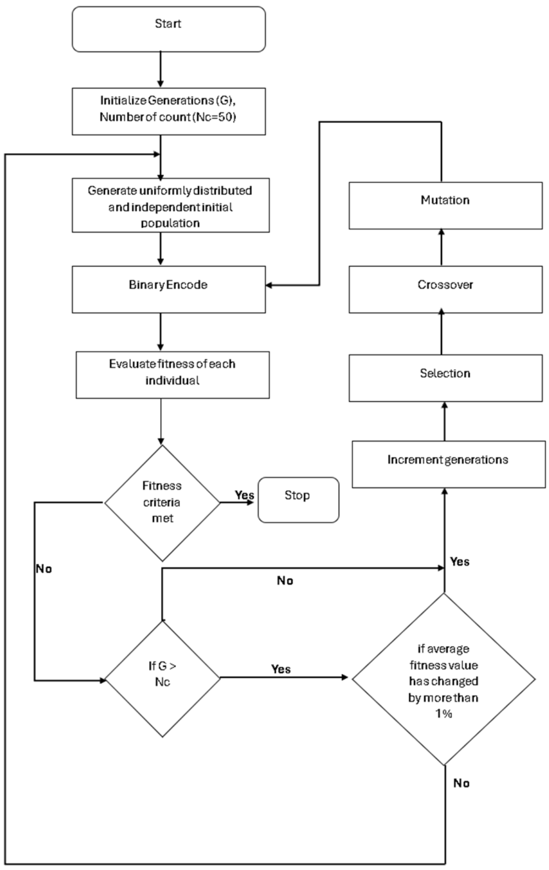


Figure 2. Flowchart for modified GA

4. EXPERIMENTAL SETUP AND TOOLS USED

In Figure 3 BS (red triangles) represent the fixed infrastructure in the network. Each BS serves the UE within its coverage area. The red circles around the BS represent their coverage areas, which are often modeled as cells. Users (blue dots) represent UE distributed randomly across the area. These users connect to the nearest BS (based on signal strength, SINR, or another metric). Coverage areas (red circles) indicate the approximate range within which each BS can effectively serve users. The overlapping circles shows where users might get interference from signals coming from BS. The simulation is like a map, with the x and y axes showing where things are in space in meters. We put the BS in spots to cover as much area as possible and we put the users in random places to make it seem like real life. We used a network area that's 1.5 kilometers by 1.5 kilometers and the users and BS are placed randomly.

To make sure we get the results with GA we have to choose the right settings for the simulation. The simulation setup and parameter configuration for the modified GA-based power optimization were selected in accordance with the specifications reported in [20]. Smaller populations can result in faster convergence and premature convergence to local optima, whereas higher populations provide more genetic diversity and a better chance of achieving the global optimum, but at a higher computational cost. As a result, the population size was set at 100. Low mutation rates can hinder the algorithm from expanding into new sections of the search space, resulting in stagnation. The rate of change should be between 0.001 and 0.01. The mutation rate should generally be set between 0.001 and 0.01. If the population lacks diversity or is locked in local optima, apply a greater mutation rate. Low crossover rates inhibit genetic recombination, potentially limiting research. High crossover rates facilitate genetic diversity but may necessitate balance with mutation. As a result, the crossover rate should typically range between 0.7 and 0.9.

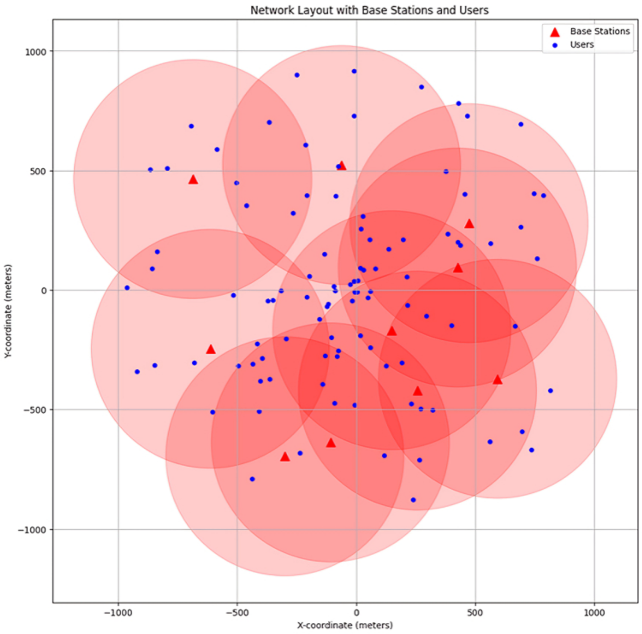


Figure 3. Simulation model

5. RESULTS FOR POWER OPTIMIZATION IN 700 MHZ AND 3500 MHZ NETWORKS MODIFIED GA

Power optimization using GA is a powerful technique for mitigating interference in 5G networks. By leveraging the principles of natural selection and evolutionary biology, GA optimizes the power allocation of BS and user devices in a way that reduces interference and enhances network performance. Modified GA uses a fitness function to evaluate solutions based on desired objectives, such as maximizing SINR or minimizing total interference in the network. By optimizing power levels, modified GA ensures that each user device and BS transmits only the necessary power to achieve reliable communication, avoiding excessive power that leads to interference.

5.1. Spectral efficiency

Spectral efficiency reflects the effectiveness of bandwidth utilization for data transmission. In Figure 4 modified GA and ML optimization techniques are used for power optimization, resulting in improved performance. Modified GA optimization is the most effective for maximizing spectral efficiency, especially at moderate SINR levels. At very high SINR, the benefits of optimization techniques are less pronounced, as the system is already operating near its capacity limits. Power optimization helps in reducing the unwanted power from nearby cells and stations and thus reducing the interference and helping in the improvement of SINR.

From Figure 4 it is observed that modified GA optimization consistently outperforms ML optimization in terms of spectral efficiency. At 700 MHz, GA achieves an improvement of approximately $\sim 1.6\%$ in maximum spectral efficiency and $\sim 4\%$ at low SINR (-5 dB). At 3500 MHz, the advantage becomes more pronounced, with GA yielding $\sim 6\%$ higher maximum spectral efficiency and up to $\sim 18\%$ improvement at low SINR conditions.

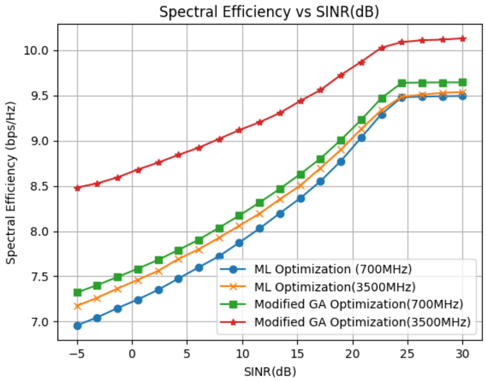


Figure 4. Spectral efficiency comparison of modified GA and ML optimization at 700 MHz and 3500 MHz across varying SINR levels

5.2. Success probability

In Figure 5 shows that modified GA optimization improves the success probability. At low SINR threshold high number of users achieve the targeted SINR and hence the success probability is higher but at higher values of SINR threshold less number of users achieve the targeted SINR, but modified GA optimization helps in reducing the interference by allocation of optimal values and hence increase the SINR. Modified GA-based optimization often performs better than ML-based optimization in 5G power allocation due to its ability to handle dynamic, non-linear, and constraint-heavy problems without reliance on training data. At low $\mathrm{SINR_T}$ (-5 dB), both techniques achieve nearly perfect success probability, with modified GA providing only marginal improvement ($\sim 1\%$ at 700 MHz and negligible at 3500 MHz). However, at high $\mathrm{SINR_T}$ (30 dB), modified GA demonstrates a clear advantage, yielding improvements of $\sim 16\%$ at 700 MHz and $\sim 13\%$ at 3500 MHz compared to ML.

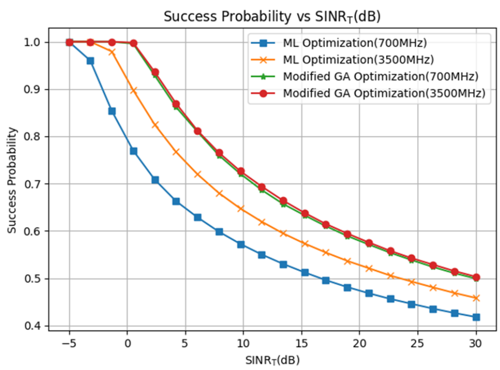


Figure 5. Success probability vs. $\mathrm{SINR_T}$ for modified GA and ML optimization at 700 MHz and 3500 MHz

5.3. Power consumption

In Figure 6 lower frequency (700 MHz) exhibits better propagation and lower attenuation, requiring less power to achieve higher SINR_T compared to the higher frequency (3500 MHz). Modified GA requires less transmission power to reach the target SINR, meaning it makes more efficient use of resources. The modified GA consistently achieves lower power consumption compared to ML, with an improvement of approximately 18% at 700 MHz and 14% at 3500 MHz, highlighting its effectiveness in power optimization. From the figure it shows that the modified GA reduces operational costs, enhances sustainability (lower carbon footprint), and maintains service quality, making it better suited for large-scale 5G deployments.

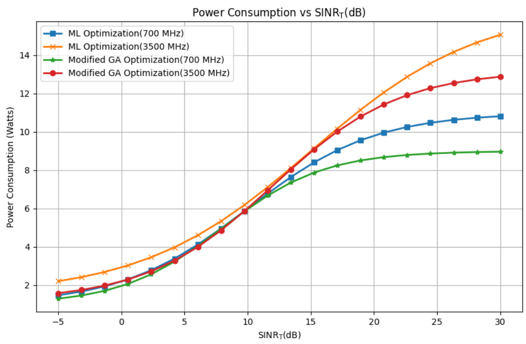


Figure 6. Power consumption comparison of modified GA and ML techniques with respect to SINR_T at various frequencies

5.4. Power efficiency

In Figure 7 modified GA optimization achieves slightly higher power efficiency compared to ML at both 700 and 3500 MHz. This is because GA better optimizes transmit power while maintaining a high spectral efficiency. 3500 MHz generally has a slight advantage over 700 MHz in energy efficiency in high-demand data. 700 MHz Band experiences lower spectral efficiency due to narrower bandwidth and congestion in high-traffic areas and thus has lower energy efficiency under heavy loads. 3500 MHz band provides higher spectral efficiency and ensures better performance under heavy traffic, improving energy efficiency when normalized to user throughput. As SINR increases, power efficiency improves across all cases. This is because a higher SINR allows better spectral efficiency and optimized power allocation minimizes waste. Modified GA-based power optimization significantly reduces transmit power consumption compared to ML, leading to better power efficiency, especially at lower SINR values where interference is greater. At low SINR (-5 dB), modified GA achieves improvements of approximately $\sim 33\%$ at 700 MHz and $\sim 25\%$ at 3500 MHz over ML, indicating better energy utilization under poor channel conditions. At high SINR (30 dB), modified GA continues to outperform ML with gains of about $\sim 30\%$ at 700 MHz and $\sim 28\%$ at 3500 MHz. This highlights the scalability of the modified GA in leveraging higher SINR conditions.

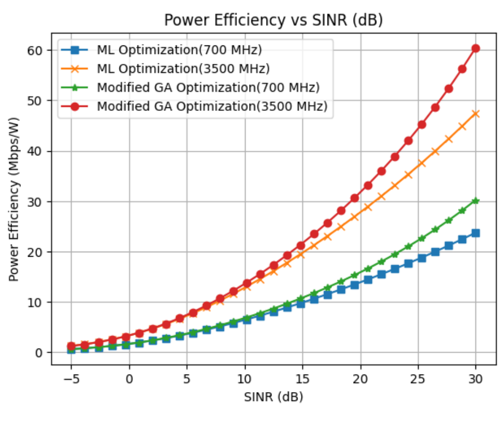
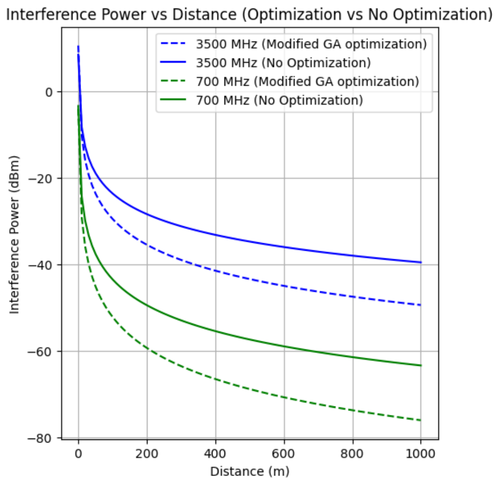


Figure 7. Power efficiency (Mbps/W) vs. SINR (dB) for modified GA and ML at 700 MHz and 3500 MHz

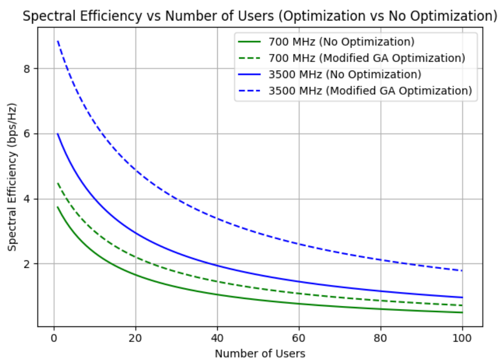
6. RESULTS FOR INTERFERENCE CANCELLATION USING POWER OPTIMIZATION

Interference in 5G networks arises when neighboring cells transmit signals at high power levels, causing overlapping frequencies or from macrocell and femtocell. Unoptimized power levels not only degrade SINR but also reduce spectral efficiency and user experience. From the above results, it is evident that modified GA performs better than ML algorithms for power optimization and helps users to allocate optimal power. Figure 8(a) highlights the effectiveness of GA optimization in mitigating interference and the differences in interference behavior across frequency bands and illustrates the relationship between interference power (measured in dBm) and distance (measured in meters) for two frequency bands, 3500 MHz and 700 MHz, under two conditions: with and without optimization using a modified GA. Interference power decreases as distance increases for all scenarios. For both frequency bands, the GA optimization significantly reduces interference power compared to no optimization. The 700 MHz band experiences lower interference power overall compared to the 3500 MHz band, due to propagation characteristics of lower frequencies. Figure 8(b) demonstrates the relationship between spectral efficiency (measured in bps/Hz) and the number of users for two frequency bands, 700 MHz and 3500 MHz, under two conditions: with and without optimization using a modified GA.

In real-world 5G networks, the key to achieve higher capacity, low latency and masive connectivity among devices is by deploying more small cells in urban areas. However, when cells are closely packed, interference between neighboring cells becomes a major challenge, potentially reducing network performance. Modified GA based power optimization technique helps in interference cancellation by optimizing transmit power and hence increases the spectral efficiency which allows more users to accomodate in a particular cell. By controlling interference through power optimization, cells can be deployed closer together without degrading each other's performance.



(a)



(b)

Figure 8. Comparison of (a) interference power vs distance and (b) spectral efficiency vs number of users

7. CONCLUSION

This paper has examined the critical role of power optimization in 5G networks, emphasizing the use of modified GA as an effective solution for balancing energy efficiency with QoS. By leveraging evolutionary search principles, the proposed approach demonstrated the ability to address non-linear, multi-objective optimization problems inherent in 5G deployments. Compared to traditional ML methods, the GA-based solution reduces dependence on large training datasets, offers flexibility in adapting to changing network conditions, and provides interpretable configurations for transmission power and user association. The usage of 700 MHz and 3500 MHz band shows we need to think about energy when planning for coverage, capacity and long-term operation. In the future there are ways to make this work even better. One way is to combine our method with reinforcement learning or deep learning to make it faster and better at adapting in time. We can also use detailed energy models that include things like the power used by hardware and cooling systems to get a clearer picture of total energy use. Another step is to test our simulation with dense and varied networks, massive MIMO and millimeter-wave technology to make sure it works well in future network setups. Lastly testing our approach, in networks and edge computing setups will help us see if it can really work in the real world and make it better. Through these future directions, the modified GA framework can evolve into a robust, intelligent optimization tool that not only advances 5G sustainability but also lays the groundwork for energy-efficient solutions in 6G and beyond.

FUNDING INFORMATION

Authors state no funding involved.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C	: **C**onceptualization	I	: **I**nvestigation	Vi	: **Vi**sualization
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Va	: **Va**lidation	O	: Writing - **O**riginal Draft	Fu	: **Fu**nding Acquisition
Fo	: **Fo**rmal Analysis	E	: Writing - Review & **E**diting		

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Derived data supporting the findings of this study are available from the first author A.G. on request.

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