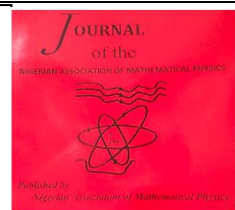


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ARTIFICIAL INTELLIGENCE ENHANCED GENETIC ALGORITHM APPROACH FOR OPTIMIZING SPECTRUM ALLOCATION IN THE UHF BAND

*Ekoko, E. C and Orukpe, P. E

Department of Electrical/Electronic Engineering, University of Benin, Benin City, Nigeria. .

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ABSTRACT

The challenge of limited spectrum in the Ultra-High Frequency (UHF) band has resulted in the creation of intelligent Dynamic Spectrum Access (DSA) methods. To address multi-objective spectrum allocation problem in Cognitive Radio Networks (CRNs), this study proposes an Artificial Intelligence Enhanced Genetic Algorithm (AI-GA). Conventional Genetic Algorithms due to static control parameters experience premature convergence; to resolve this, a Feed-Forward Neural Network (FNN) was incorporated that uses real-time generation fitness data to dynamically adjust the crossover and mutation rates. The optimization framework considered five users and seven frequency bands, aimed to maximize throughput, spectral efficiency and fairness, while minimizing interference. The simulation results showed that the AI-GA achieved a Throughput of 3.78×10^5 bps, Spectrum Efficiency of 5 bps/Hz, Fairness Index of 0.98 and consistent interference minimization of 90 dB. The proposed model outperformed conventional GA and other AI-enhanced methodologies by dynamically balancing exploration and exploitation, providing a reliable solution for fair and effective spectrum management. The results demonstrated that using neural networks to dynamically adjust GA parameters significantly improves Genetic Algorithms' search capabilities, which makes the proposed AI-GA framework suitable for dynamic interference sensitive and fairness critical cognitive radio environments..

1. INTRODUCTION

Wireless communication services depend on the radio frequency (RF) spectrum, a limited natural resource [1]. The current spectrum management is based on a rigid division known as the fixed or static spectrum access. In the fixed spectrum access, the spectrum must be divided into separate bands with each band's license holder having the sole right to make use of the band [2]. This fixed spectrum management policy has led to significant inefficiencies, where licensed bands like the Ultra-High Frequency (UHF) band (300MHz-3GHz) are often underutilized and the unlicensed bands like the Industrial Scientific and Medical (ISM) bands experience severe congestion and high spectrum scarcity due to the proliferation of Internet of Things (IoT) devices [3]

*Corresponding author: EKOKO E. C

E-mail address: erumena.ekoko@uniben.edu

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Addressing the issues associated with the licensed and the unlicensed frequency spectrum led to the Cognitive Radio (CR) technology implementation which has emerged as a promising solution. This solution is enabled by Dynamic Spectrum Access (DSA) which makes it possible for unlicensed (secondary) users to opportunistically access idle licensed spectrum (Television White Spaces or Spectrum holes) without interfering with primary users [4; 5].

Cognitive Radio is a software Defined Radio (SDR) that can sense its environment and adjust its operating parameters such as transmit power, modulating scheme, power level, etc. to make use of the best idle spectrum within its vicinity [6]. The technique of allocating available channels among secondary users in order to maximize network utility is known as spectrum allocation [7], which is one of the fundamental challenges in Cognitive Radio Networks (CRNs). Spectrum allocation requires robust optimization techniques for its implementation in a CRN. Although conventional heuristic methods like Genetic Algorithms (GA) (a searched based optimization method inspired by genetics and natural selection), that evolves a population of potential solutions through processes like selection, crossover and mutation) have been employed, such techniques frequently experience premature convergence and become stuck in local optimal because of the static parameter values.

In [8], the authors developed a hybrid optimization technique that combines Ant Colony Optimization (ACO), Genetic Algorithm (GA), and Firefly Algorithm (FA) for TV White Space networks. Their FAGAACO technique results showed that it outperformed conventional hybrid techniques and enhanced exploration capabilities. However, adaptive tuning of the GA parameters using the Neural Network was not considered and also a single objective function was considered in their study. In order to optimize spectrum allocation in CR networks, [9] used Genetic Algorithm to maximize battery life and communication connection quality in CRNs. Their findings showed an increase in the efficiency of spectrum utilization; however, the study did not use Artificial Intelligence to dynamically adjust the GA parameters (mutation and crossover rates), which could limit the quality of the solution in complicated, interference-prone scenarios. Authors in [10] introduced the Non-dominated Sorting Genetic Algorithm based on Reinforcement Learning (NSGA-RL). It used a self-tuning parameter strategy to manage several competing goals, such as Spectral Efficiency and network capacity. However, instead of using a Feed Forward Neural Network for direct parameter prediction as this present study proposes, their study mostly concentrated on Reinforcement Learning integration. Furthermore, an adaptive system to changing network conditions was not considered in their study. GA is being utilized for optimization in a highly dynamic telecommunication environment. Hence, in order to improve on the conventional GA to achieve better convergence and prevent the algorithm from getting stuck in local optimal solutions (by striking a balance between exploration and exploitation), this paper proposes an Artificial Intelligence Enhanced Genetic Algorithm (AI-GA) to optimize spectrum allocation in the UHF band. This enhanced GA technique incorporates a Feed-Forward Neural Network (FNN) for dynamic adjustment of the GA parameters. The Feedforward Neural Network enables Genetic Algorithm to dynamically adjust its parameters based on past fitness history on adaptive environmental feedback. This adaptive strategy seeks to minimize interference while maximizing throughput, spectral efficiency, and fairness simultaneously in a multi-user UHF environment.

2. METHODOLOGY

The Artificial Intelligence Enhanced Genetic Algorithm (AI-GA) was used in this study to optimize UHF band spectrum allocation. Using Python 3 on the Google Colaboratory platform, the simulation environment was created using libraries like NumPy for numerical analysis and

TensorFlow/Keras for the neural network component. The system size comprises of five users (N=5), seven available spectrum bands (M=7) and the bandwidth required by each user was randomly generated between 470 and 870MHz. In order to provide a controlled environment for proof-of-concept testing without excessive initial computational overhead, five users (N=5) and seven available spectrum bands (M=7) were chosen to mimic a typical small-scale cognitive radio cell or a particular UHF sub-band situation.

The methodology involved generating synthetic data, initialization of the GA parameters, using Neural Network to change the parameters dynamically and evaluating the results based on the performance metrics considered in this study.

2.1 Mathematical Modelling of the Adaptive Multi-Objective Function

The mathematical formulation of the four-fold adaptive multi-objective optimization of spectrum allocation was modeled. The multi-objective goal was to maximize Throughput, Spectral Efficiency, and Fairness, while minimizing Interference.

2.1.1 Objective Functions

The objective function aims to optimize total spectrum allocation by minimizing interference, while maximizing throughput, spectral efficiency and fairness. It was mathematically represented as a weighted sum of the following functions (Equations (1)-(5)) to obtain Equation (6).

Spectrum Allocation Maximization:

$$f_1(P) = \sum_{i=1}^N \sum_{k=1}^N P_{i,k} \quad (1)$$

Interference Minimization:

$$f_2(P) = \sum_{i=1}^N \sum_{j=1}^N \sum_{k=1}^N I_{ij,k} + \sum_{i=1}^N \sum_{k=1}^M N_{i,k} P_{i,k} \quad (2)$$

Ensure Fairness:

$$f_3(P) = \frac{[\sum_{i=1}^n x_i]^2}{n \sum_{i=1}^n x_i^2} \quad (3)$$

The Fairness was measured using Jain's Fairness Index, where x_i = allocation for the i_{th} user.

Throughput Maximization:

$$f_4(P) = \sum_{i=1}^N \sum_{k=1}^M \varphi_i(P_{i,k}) \quad (4)$$

where, $\varphi_i(P_{i,k}) = B_k \log_2(1 + \frac{P_{i,k}}{N_{i,k}})$ is the Shannon's theory equation.

Spectral Efficiency Maximization:

$$f_5(P) = \sum_{i=1}^N \sum_{k=1}^M \frac{\varphi_i(P_{i,k})}{P_{i,k}} \quad (5)$$

In order to achieve the adaptive multi objective function $F(P,t)$, the weighted sum of the individual objectives according to Equation (6) was used.

$$\min F(P, t) = \alpha_1(t)(-f_1(P)) + \alpha_2(t)f_2(P) + \alpha_3(t)f_3(P) + \alpha_4(t)(-f_4(P)) + \alpha_5(t)(-f_5(P)) \quad (6)$$

where $\alpha_i(t)$ = the adaptive weight parameter sensitive to network changes.

2.2 Artificial Intelligence Enhanced Genetic Algorithm Adaptive Multi-Objective Spectrum Allocation

Through the evolution of a population of potential solutions (allocation matrices), the AI-GA improves spectrum allocation. Using a Feed-Forward Neural Network (FNN) to dynamically adjust the GA parameters is the unique aspect of this method. To overcome the limitation of static parameters in conventional GA, an FNN is integrated into the GA to predict optimal crossover (Pc) and mutation (Pm) rates for each generation. The objective fitness function, which evaluates each individual of the population is a weighted sum of the total throughput and an additional term that penalizes high interference and noise levels. It is given by Equation (7):

$$\begin{aligned} \text{Fitness} &= \alpha \times \text{Total Throughput} - \beta \times \left(\sum_{i=1}^N \sum_{j=1}^M a_{ij}(I_{ij} + N_j) \right) \\ &= \alpha \left(\left(\prod_{i=1}^N \left(\sum_{j=1}^M a_{ij} B_i \log_2 \left(1 + \frac{S_i}{I_{ij} + N_j} \right) \right) \right)^{\frac{1}{N}} \right) - \beta \times \left(\sum_{i=1}^N \sum_{j=1}^M a_{ij}(I_{ij} + N_j) \right) \end{aligned} \quad (7)$$

Where the Throughput derived from the Signal to Interference plus Noise Ratio (SINR) for user i on band j is given by Equation (8):

$$\text{Throughput}_{ij} = B \log_2 \left(1 + \frac{S_i}{I_{ij} + N_j} \right) \quad (8)$$

2.2.1 Feedforward Neural Network Architecture

In order to predict crossover (Pc) and mutation (Pm) rates, the integrated Feed-Forward Neural Network (FNN) comprises of an:

- Input layer: With three neurons (current generation, mean fitness, and fitness variance).
- Hidden layers: Two hidden layers with 12 neurons each using ReLU activation.
- Output layer: With two neurons using Sigmoid activation.

2.2.2 Training Process

The dataset used for training the Feedforward Neural Network was gotten from simulation runs of the spectrum allocation model set up with the following parameters:

- 5 users
- 7 spectrum bands

The dataset came from several GA executions with different allocation scenerios and interference conditions. System level performance metrics were documented for every GA generation, such as:

- Fitness values
- Interference levels
- Throughput performance

- Allocation matrix characteristics
- Spectral efficiency metrics

As a result, each training sample included:

- Input: System and GA performance state variables.
- Target Output: The crossover and mutation parameters that correspond to high-performing generations.

A dataset of 1,000 generations' worth of fitness history collected from early "traditional" GA runs were used to train the FNN. This makes it possible for the network to identify trends in population diversity (variance) and recommend settings that encourage exploitation (more crossover) or exploration (greater mutation). Due to the utilization of simulation generated data, the neural network learns parameter adjustment strategies that are closely related to the problem environment, namely multi-objective spectrum allocation in TV White Space bands.

2.2.3 Integration of AI into the Genetic Algorithm

The neural network was incorporated into the GA evolutionary loop when training was completed. At every generation, the following was carried out:

1. Current performance metrics (Fitness, interference, and throughput) were taken out.
2. The trained neural network was fed these metrics.
3. New predicted crossover and mutation rates were generated by the network.
4. Using the adaptively tuned parameters, the GA carried out evolutionary operations.

The algorithm reacts dynamically to the optimization landscape for this closed-loop interaction, which increases convergence speed and solution stability.

2.2.4 Adaptive Equation

In the adaptation mechanism, to understand the connection between population diversity (variance) and ideal parameter settings, the FNN was trained using past fitness data. For instance, the network may raise P_m to promote exploration if variance is low, which indicates convergence. On the other hand, a high variance may raise P_c to take advantage of good solutions.

The dynamic adjustment can be represented by Equation (9):

$$[P_c(t), P_m(t)] = FNN (Gen_t, \mu_{fitness}, \sigma_{fitness}^2) \quad (9)$$

where t = current generation.

The Noise level and Interference matrices used to compute the AI-GA simulation and penalty are given in Equations (10) and (11) respectively, while the flowchart for developing the AI-Enhanced Genetic Algorithm Optimized Spectrum Allocation is shown in Figure 1.

$$P_{n,m} = \begin{bmatrix} 0.010 & 0.012 & 0.009 & 0.010 & 0.011 & 0.009 & 0.010 \\ 0.011 & 0.010 & 0.010 & 0.009 & 0.012 & 0.011 & 0.009 \\ 0.010 & 0.009 & 0.011 & 0.010 & 0.010 & 0.012 & 0.010 \\ 0.009 & 0.011 & 0.010 & 0.009 & 0.010 & 0.010 & 0.011 \\ 0.010 & 0.010 & 0.009 & 0.011 & 0.010 & 0.009 & 0.010 \end{bmatrix} \quad (10)$$

$$I_{n,m} = \begin{bmatrix} 0.08 & 0.10 & 0.07 & 0.05 & 0.11 & 0.09 & 0.06 \\ 0.09 & 0.12 & 0.10 & 0.07 & 0.10 & 0.11 & 0.08 \\ 0.10 & 0.11 & 0.09 & 0.06 & 0.12 & 0.08 & 0.07 \\ 0.07 & 0.09 & 0.08 & 0.10 & 0.09 & 0.07 & 0.11 \\ 0.11 & 0.08 & 0.09 & 0.07 & 0.10 & 0.09 & 0.08 \end{bmatrix} \quad (11)$$

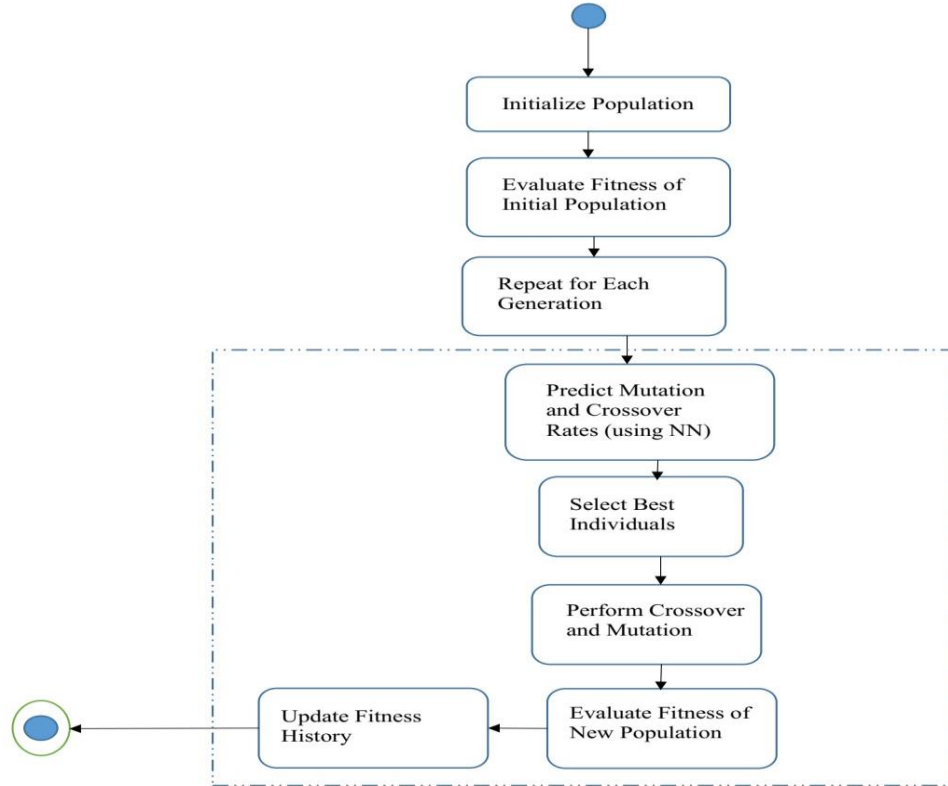


Figure 1: Flowchart for AI-Enhanced Genetic Algorithm Optimized Spectrum Allocation

Figure 1 depicts the flowchart where the conventional GA passes its fitness history to the Neural Network, which in return predicts new P_c and P_m values for the next generation crossover and mutation step.

RESULTS AND DISCUSSION

To optimize the allocation of seven spectrum bands among five users, the AI- Enhanced Genetic Algorithm (AI-GA) was tested over a 100 generations. The model was able to converge well in terms of analyzing the performance metrics for minimizing Interference, maximizing Throughput, Spectral Efficiency and Fairness due to the neural network’s dynamic adaptation of crossover and mutation rate.

3.1 Optimized Spectrum Allocation for AI-GA Model

The binary allocation matrix was generated by the AI-GA. A channel is assigned if the value is '1' and there is no assignment if the value is '0'. Notably, in order to reduce interference and increase overall system fairness, User 3 (third row in Equation (12)) was not assigned any band in the final optimized allocation. This is because the system intelligence determines that an allocation to User 3 will cause interference among other users, as User 3 had the highest level of perceived interference in the simulated environment. Figures 2-5 were obtained for the metrics considered.

$$Allocation_{AI-GA} = \begin{bmatrix} 0 & 1 & 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 1 \end{bmatrix} \quad (12)$$

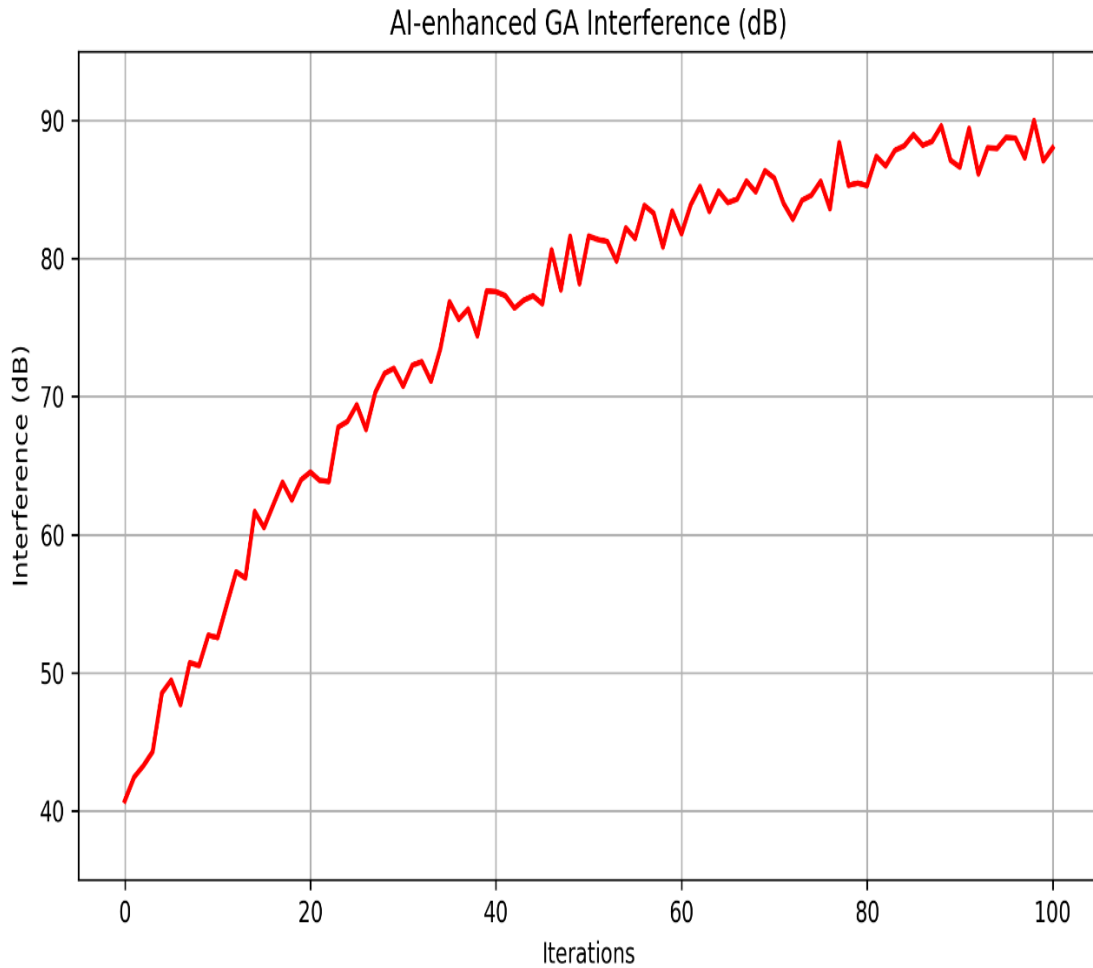


Figure 2: Interference for AI-Enhanced Genetic Algorithm

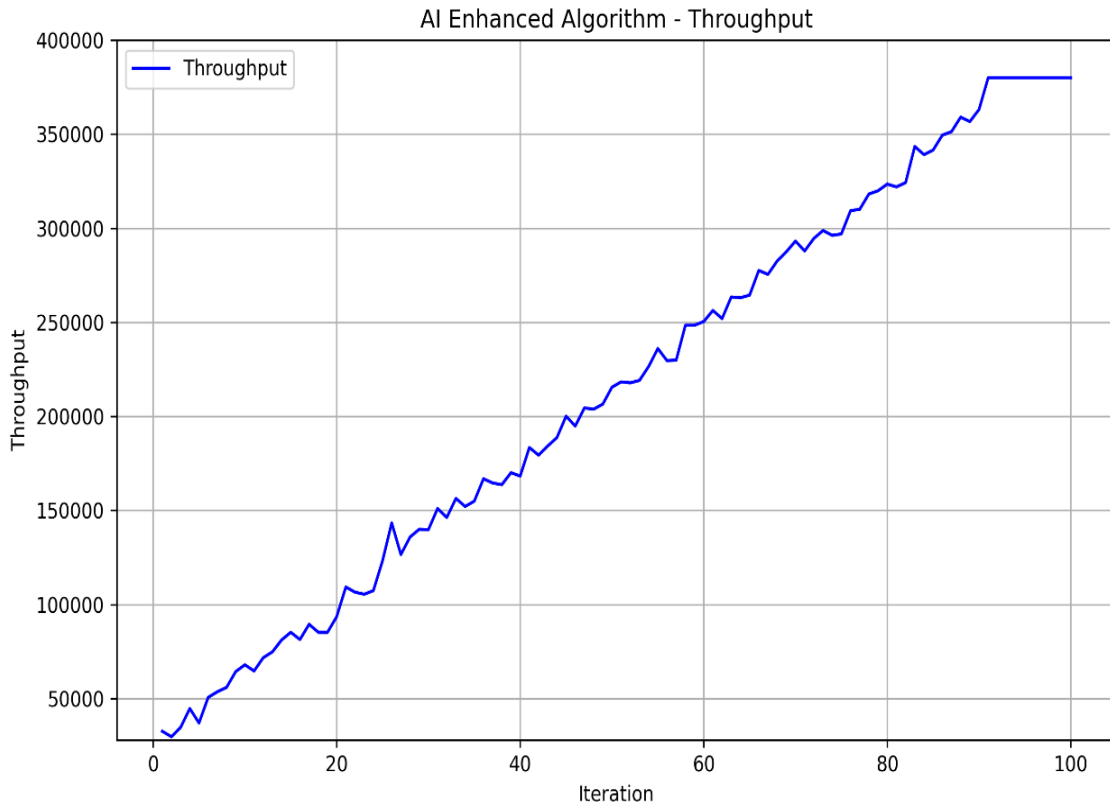


Figure 3: Throughput for AI-Enhanced Genetic Algorithm

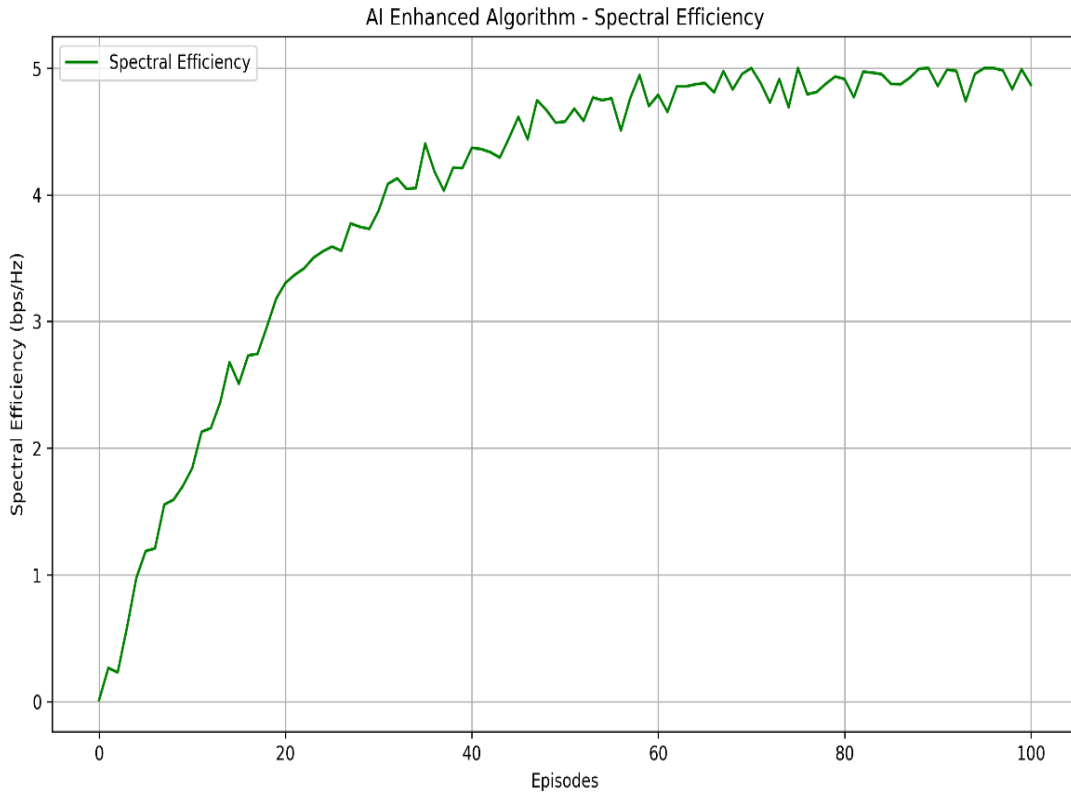


Figure 4: Spectral Efficiency for AI-Enhanced Genetic Algorithm

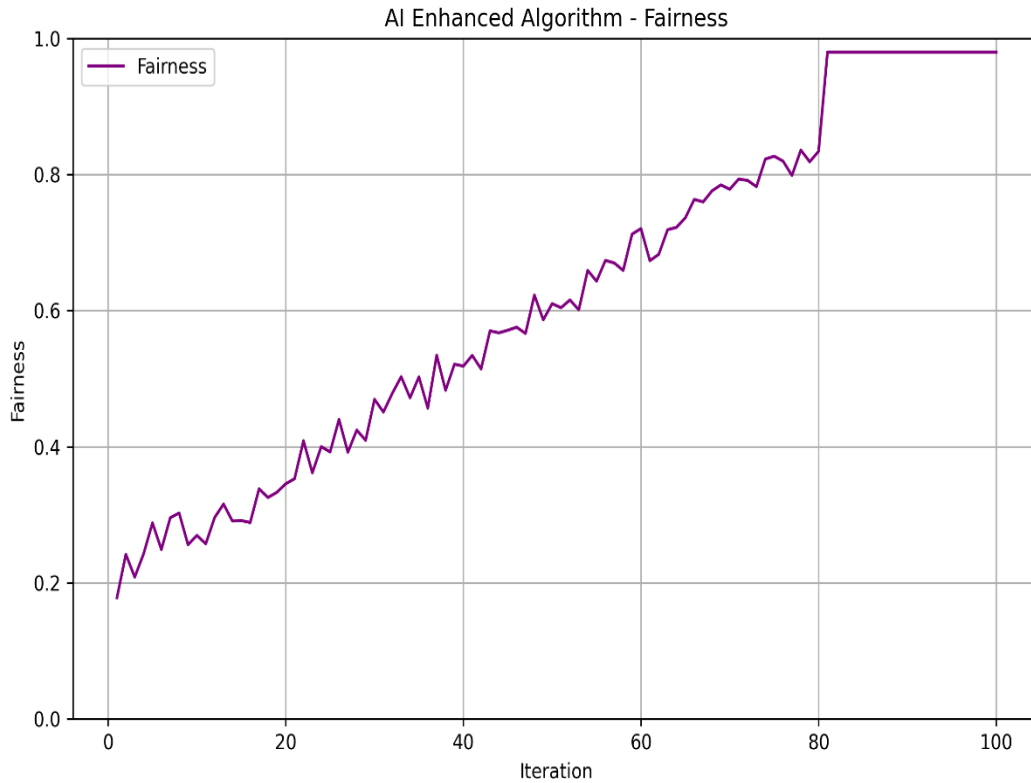


Figure 5: Fairness for AI-Enhanced Genetic Algorithm

3.2 Discussion of Results

The performance of the AI-GA was tracked across 100 iterations (generations) and the discussion for the performance metrics is as presented.

3.2.1 Interference (dB)

Robust minimization of Interference was shown using the AI-GA model. As shown in Figure 2, it minimized interference from ~ 40 dB and steadily improved minimization of interference until it reaches an optimal value of 90 dB at the 88th iteration. It continued to oscillate about this value until the 100th iteration. The advantage of adaptive evolutionary operators is demonstrated by the convergence to 90 dB interference minimization. The algorithm successfully isolated User 3 to safeguard the signal quality of others by avoiding local optimum where high interference might be tolerated by dynamically modifying mutations rates. According to the AI-GA, giving User 3 any band would severely impair the system's overall signal-to-interference-plus-noise ratio (SINR), lowering the Fairness Index below 0.90 and raising overall interference. As a result, eliminating User 3 maintained an overall Fairness Index of 0.98 while optimizing the utility for the other four users.

3.2.2 Throughput (bps)

At the 90th iteration (Figure 3), Throughput reached a constant maximum value of 378000 bps, up from an initial rate of about 25000 bps. The Neural Network's capacity to predict optimal parameters that speed up the search process is responsible for this fast convergence. By the 90th generation, the AI-GA had achieved its ideal throughput and stability. Due to dynamic parameter

tuning, the AI-GA converges in less than half the time required by conventional GAs, which frequently take 200 to 500 generations to escape local optimal in comparable multi-objective scenarios.

3.2.3 Spectral Efficiency (bps/Hz)

As shown in Figure 4, Spectral Efficiency improved steadily starting with the 1st iteration, peaking at 5 bps/Hz at the 67th iteration and remained at this value until the end of the simulation. The Neural Network’s capacity to predict optimal parameters that speed up the search process is responsible for this fast convergence (in contrast to conventional GAs, which frequently need hundreds more generations).

3.2.4 Fairness Index

At the 82nd iteration (Figure 5), the Jain’s Fairness Index increased from 0.2 to 0.98, demonstrating a very fair allocation of resources among the designated users. The Fairness value obtained, guarantees that the algorithm provides a balanced solution where many users (Users 1, 2, 4 and 5) receive allocations altogether, rather than some just maximizing total throughput while starving other users with worse channel conditions.

The high fairness and interference minimization makes this AI-GA approach dependable for quality sensitive applications, even though the throughput 378000 bps is lower than what might be achieved by purely greedy methods. Furthermore, the results confirm how well the AI-Enhanced GA handles the complex, multi-objective nature of spectrum allocation.

From the results, it is seen that the AI-GA framework has scalability built in, as the integrated Feed-Forward Neural Network (FNN) mitigate the exponential expansion of the Genetic Algorithm's search space caused by an increase of users or bands by dynamically modifying crossover and mutation rates to avoid premature convergence in bigger, more complicated populations. Once trained, the FNN can anticipate parameters in real-time deployments with sub-millisecond accuracy, which makes the system viable for dynamic network situations.

3.3 Validation of the AI-GA Result with Existing Works

The AI-GA performance was evaluated against other conventional GA and Enhanced GA techniques found in literature as presented in Table 1.

Table 1: Validation of Proposed AI-GA Model against Existing Works

Author	Technique Used	Metric of Comparison	Literature Result/ Present Study Result
[10]	NSGA-RL (AI-Enhanced)	Spectral Efficiency	~0.38 bps/Hz/5 bps/Hz
[9]	Traditional GA	Interference	24 dB/90 dB
[11]	Hybrid Fuzzy GA	Interference	69 dB/90 dB

From Table 1, it is seen that the proposed technique of enhancing GA with Feedforward Neural Network to dynamically adjust the GA parameters, surpassed the outcomes from existing works considered. This shows that dynamically adjusting the GA parameters, and taking advantage of the predictable nature of NNs, can effectively address the issues associated with the conventional GA. Such techniques are therefore highly effective in a high dynamic environment. Also compared to conventional heuristic approaches, the FNN's overall reduction in the number of generations considerably reduces the total computational time needed to arrive at a stable optimal solution, despite the fact that it adds a small computing step for parameter prediction to each generation.

CONCLUSION

In order to optimize spectrum allocation in the Ultra-High Frequency (UHF) band, this study successfully developed and applied an Artificial Intelligence Enhanced Genetic Algorithm (AI-GA). The proposed technique addressed the drawbacks of conventional heuristic techniques, which frequently experience premature convergence and static parameter rigidity. The AI-GA incorporated a Feed-Forward Neural Network (FNN) to dynamically change the crossover and mutation rates of the Genetic Algorithm. The AI-GA framework provides a reliable solution for Cognitive Radio Networks based on the simulation results. It attained a constant Throughput of 3.78×10^5 bps and a Fairness Index of 0.98. The AI-GA showed better convergence stability and fair resource distribution than other approaches, which makes it especially appropriate in situations where interference minimization and fairness are more important than raw throughput maximization. Conclusively, it is found that in complicated multi-objective optimization scenarios, the search capability of Genetic Algorithms is greatly improved by the dynamic adaptation of evolutionary parameters by Deep Learning. However, some limitations observed include: increasing computational complexity with network expansion, dependence on synthetic simulation data and improved parameter adaptation procedure in real-time hardware context. Future research should employ this proposed model to other datasets involving real world data, other Spectrum allocation objectives such as Quality of Service could be considered and finally Reinforcement Learning agents should be incorporated to further strengthen the robustness and scalability of this proposed model.

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