Transactions of NAMP 24, (2026) 89-100

Transactions of
The Nigerian Association of
Mathematical Physics
Journal homepage: https://nampjournals.org.ng

OPTIMIZATION OF UHF SPECTRUM ALLOCATION LEVERAGING DEEP LEARNING

[1*]Ekoko, E. C. and [2]Chinaeke-Ogbuka, I. M.
[1]*Department of Electrical/Electronic Engineering, University of Benin, Benin City, Nigeria.*
[2]*Department of Electronics and Computer Engineering, University of Nigeria, Nsukka.*

ARTICLE INFO

Article history:
Received xxxxx
Revised xxxxx
Accepted xxxxx
Available online xxxxx

Keywords:
Deep Neural Network,
Cognitive Radio,
UHF Spectrum Allocation,
Performance Metrics.

ABSTRACT

The study addresses spectrum scarcity and congestion caused by static spectrum management and the deployment of Internet of Things (IoT). To address these issues, this study proposes a Deep Learning based framework for Dynamic Spectrum Access (DSA) using Deep Neural Network (DNN) optimized with the Levenberg-Marquardt algorithm to solve an adaptive multi-objective spectrum allocation problem. The DNN treats allocation as a classification task, effectively mapping interference patterns and user demands as real-time channel assignments, unlike conventional heuristic approaches that depend on recurrent search. The model focused on five secondary users and seven frequency bands, to maximize throughput, spectral efficiency, and fairness while minimizing interference. The simulation results demonstrated a Spectral Efficiency of 10 bps/Hz, a Throughput of $1.5*10^7$ bps, a nearly flawless Fairness Index of 1.00 and attaining minimal interference of 90 dB, outperforming current state-of-the-art techniques and showcasing its potential for reliable and fair spectrum management in next-generation cognitive radio networks.

1. INTRODUCTION

Radio frequency (RF) spectrum refers to a range of frequencies within the electromagnetic spectrum. It is a finite resource in the range of frequency from 3 kHz to 300 GHz which is used for wireless communication and services. Fixed spectrum access paradigm, in which frequency bands are statically assigned to authorized users (primary users), has historically been the foundation of spectrum management [1]. However, the Internet of Things (IoT) and mobile networks have grown exponentially, exposing the inefficiencies of this inflexible structure and creating an artificial scarcity paradox where licensed bands are severely congested and continue to be underutilized [2; 3]. Cognitive Radio (CR) technology, an intelligent wireless communication system that can sense its environment and modify its operational parameters (frequency, power, modulation) to maximize performance [4; 5] has emerged as a solution to this inefficiency.

---

[*]Corresponding author: EKOKO E. C.
E-mail address: erumena.ekoko@uniben.edu

https://doi.org/10.60787/tnamp.v24.670

1115-1307 © 2026 TNAMP. ALL RIGHTS RESERVED

This enables Dynamic Spectrum Access (DSA) by enabling secondary users to take advantage of Television White Spaces (TVWS) utilization, which are idle parts of the UHF spectrum at a particular time and location; that have been vacated by TV stations due to migration from analog to digital broadcasting [6; 7]. Spectrum allocation, the intricate process of allocating available channels among secondary users in order to improve system throughput and spectral efficiency while minimizing interference, is the main problem in CR networks [8]. Although heuristic optimization techniques like Genetic Algorithms (GA) have been extensively studied for this purpose, their high processing costs during real time convergence are a common problem. Also, majority of existing studies have used the Artificial Intelligence techniques even the Deep Neural Network for optimized spectrum allocation but an adaptive AI system that handles many conflicting goals of Interference minimization, Spectral Efficiency, Throughput and Fairness maximization is a huge limitation. A viable substitute is provided by Deep Neural Networks (DNN), which use pattern recognition to translate complicated channel state data into the optimal allocation decision. A hybrid heuristic (FAGAACO) was developed by [9] for TV White Space networks, their study introduced a hybrid optimization technique called Firefly Algorithm, Genetic Algorithm and Ant Colony Optimization (FAGAACO). The method surpassed conventional algorithms in spectrum efficiency and enhanced exploring capabilities. However, it retained the significant computational expense of complicated hybrid heuristic search spaces and relied on a single-objective fitness function. In [10], the authors presented a method for channel allocation for underlay CRNs that makes use of Deep Neural Networks. They trained a DNN to manage co-channel interference by framing the allocation problem as a non-convex optimization task. Their model validated the speed advantage of DNNs for real-time decision making by showing 98.4% spectrum access efficiency and 85% reduction in calculation time when compared to conventional iterative approaches. For multi-channel CRNs, the author in [11] proposed a DNN-based resource allocation strategy. The model was developed to strictly limit interference to primary users while optimizing the spectral efficiency of secondary users. The practicality of deep learning for complicated constraint management was demonstrated, in that the DNN could successfully anticipate total transmit power and channel distribution, attaining excellent spectral efficiency while maintaining acceptable interference levels. This paper focuses on the development and evaluation of an adaptive DNN-based framework for UHF spectrum allocation optimization handling four-fold performance metrics of minimizing Interference, while maximizing Throughput, Spectral Efficiency and Fairness. In contrast to repetitive heuristic searches, the proposed DNN model maximizes spectral efficiency and fairness in an adaptive multi-user environment scenario by instantly predicting appropriate channel assignments using Feed-Forward classification approach.

2. METHODOLOGY

In order to optimize the adaptive spectrum allocation in the UHF band, this study used a Deep Neural Network (DNN) framework. The experimental environment for developing the models was the Google Colaboratory environment, libraries like TensorFlow, Keras, and NumPy were used for numerical computation. The system comprised of five users (N=5) and seven available spectrum bands (M=7). The bandwidth required by each user was randomly generated between 470 and 870 MHz. An interference and noise level matrices were also randomly generated considering number of users, available spectrum bands and user bandwidth. The methodology follows a pipeline of synthetic data generation, model training, and performance evaluation as shown in Figure 1.

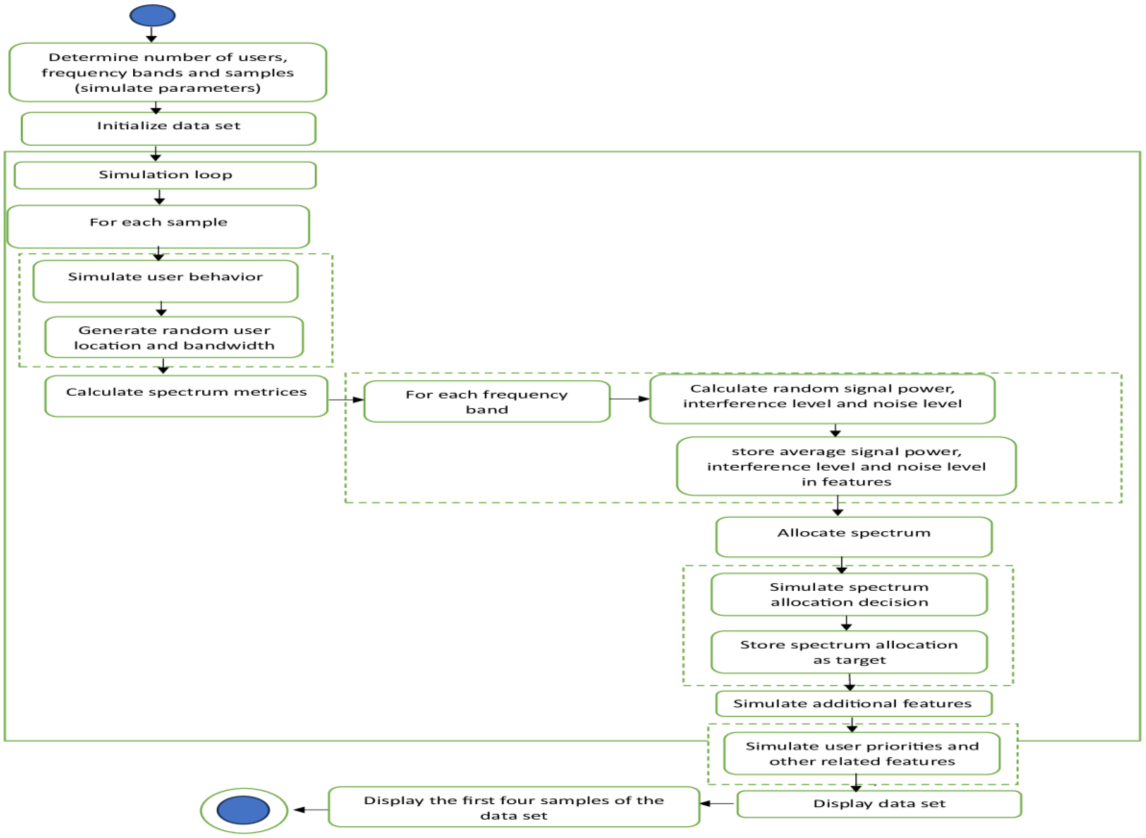

Figure 1: Flowchart for Deep Neural Network Spectrum Simulation

Figure 1 shows the flowchart illustrating the simulation process: Data Generation (User bandwidths, Interference matrices), Data Splitting (80% Training, 20% Testing), DNN Model (Input: Receives a flattened vector of features representing channel gains and interference; Hidden Layers: Two dense layers with 128 and 64 neurons utilizing the ReLU activation function; Output Layers: Uses Softmax function to output a probability over the 7 bands for each user).

2.1 General System Model and Mathematical Problem Formulation

The spectrum allocation problem was modeled as a multi-objective optimization problem aimed at maximizing network efficiency while satisfying user constraints.

2.1.1 Objective Functions

The objective function seeks to optimize total spectrum efficiency by minimizing interference (I) and maximizing throughput (T), spectral efficiency (η) and fairness (F). The mathematical representation for the objective function is a weighted sum of the entire functions (Equations (1)-(4) and Equation (6)) given by Equation (7).

2.1.1.1 Spectrum Allocation Maximization

This is represented by Equation (1):

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

2.1.1.2 Interference Minimization

The interference function to be minimized is defined as the sum of mutual interference and noise penalties given by Equation (2):

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

2.1.1.3 Fairness Maximization

Fairness among users is quantified using Jain's Fairness Index given by Equation (3):

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

where x_i = throughput allocation for the i_{th} user.

2.1.1.4 Throughput Maximization

This is given by Equation (4):

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

The throughput for user *i* on band *k* is calculated using Shannon's capacity formula given by Equation (5):

$$\emptyset_i(P_{i,k}) = B_k \log_2\left(1 + \frac{S_i}{I_{ij,k} + \mathrm{N}_{i,k}}\right) \tag{5}$$

where, $\emptyset_i(P_{i,k})$ = Throughput; $P_{i,k}$= binary allocation variable (1 if assigned, 0 otherwise); S_i = signal power; $I_{ij,k}$ = interference from user *j;* $\mathrm{N}_{i,k}$= noise level.

2.1.1.5 Spectral Efficiency Maximization

This is represented by Equation (6):

$$f_5(P) = \sum_{i=1}^{N}\sum_{k=1}^{M}\frac{\varphi_i(P_i,k)}{P_i,k} \tag{6}$$

The adaptive multi-objective function given by Equation (7) is obtained by combining the functions represented in Equations (1)-(4) and Equation (6).

$$Min\ F(P,t) = \alpha_1(t)(-f_1(P)) + \alpha_2(t)f_2(P) + \alpha_3(t)f_3(P) + \alpha_4(t)(-f_4(P)) + \alpha_5(t)(-f_5(P)) \tag{7}$$

Adaptability of the system is further given by Equation (8) as:

$$\alpha_i(t) = \alpha_i^{obj} + \alpha_i \phi_i(t) \tag{8}$$

where $\alpha_i \phi_i(t)$= the dynamic nature of the channel or the function that captures network changes.

2.2 Deep Neural Network Adaptive Multi-Objective Spectrum Allocation

The DNN model handles spectrum allocation as a multi-class classification problem, mapping complex environmental states (interference patterns, noise levels) to optimal channel assignments.

2.2.1. DNN Training Data Generation

In order to simulate realistic wireless network behavior, synthetic data were created because real-world tagged spectrum datasets were absent.

2.2.1.1 Input Feature

1000 samples in all were generated. Three 5x7 matrices were created for every sample of: Channel Gain Matrix (A), Interference Matrix (I), Noise Power Matrix (P).

$$A_{n,m} = \begin{cases} 1, & if\ user\ n\ is\ assigned\ to\ band\ m \\ 0, & if\ assignment\ is\ otherwise \end{cases} \tag{9}$$

The Interference Matrix ($I_{n,m}$) used for the DNN simulation is given by Equation (10). While the Noise Matrix ($P_{n,m}$) for the thermal and background noise floor at each user-band pair is given by Equation (11).

$$I_{n,m} = \begin{bmatrix} 0.12 & 0.10 & 0.15 & 0.20 & 0.08 & 0.11 & 0.09 \\ 0.11 & 0.13 & 0.09 & 0.14 & 0.10 & 0.16 & 0.07 \\ 0.10 & 0.12 & 0.11 & 0.09 & 0.13 & 0.08 & 0.10 \\ 0.15 & 0.09 & 0.13 & 0.11 & 0.12 & 0.07 & 0.14 \\ 0.08 & 0.14 & 0.10 & 0.13 & 0.11 & 0.09 & 0.12 \end{bmatrix} \tag{10}$$

$$P_{n,m} = \begin{bmatrix} 0.100 & 0.100 & 0.090 & 0.110 & 0.100 & 0.120 & 0.090 \\ 0.110 & 0.090 & 0.100 & 0.120 & 0.100 & 0.110 & 0.100 \\ 0.090 & 0.100 & 0.110 & 0.100 & 0.090 & 0.120 & 0.110 \\ 0.100 & 0.090 & 0.100 & 0.100 & 0.110 & 0.090 & 0.100 \\ 0.120 & 0.110 & 0.090 & 0.100 & 0.100 & 0.090 & 0.110 \end{bmatrix} \tag{11}$$

2.2.1.2 Data Spli

To guarantee accurate model generalization and objective assessment:

- 80% of the dataset was used for training
- 20% of the dataset was reserved for validation/testing

To avoid distribution bias, a stratified random sample technique was used to split the dataset. To prevent overfitting, the model used 20% test set for evaluation and during training, the validation set was strictly maintained and utilized only for: Monitoring performance, evaluation of generalization and evaluation of allocation prediction.

2.2.1.3 Training Algorithm (Levenberg-Marquardt)

The model weights are updated using the Levenberg-Marquardt backpropagation algorithm given by Equation (12), which blends the Gradient Descent and Gauss-Newton methods for faster convergence.

$$\Delta w = -(J^T J + \lambda I)^{-1} J^T e \tag{12}$$

where, J = Jacobian matrix of error derivatives, e = vector of network errors and λ = damping factor.

2.2.2 DNN Model Architecture

The architecture consists of:

2.2.2.1 Input Layer

The dimension equivalent to the three 5x7 matrices' flattened feature vector.

2.2.2.2 Hidden Layers

The hidden layers are:

- First Hidden Layer: 128 neurons, ReLU activation

- Second Hidden Layer: 64 neurons, ReLU activation.

Due to the DNN processing efficiency and capacity to mitigate vanishing gradient problems, the ReLU activation function was chosen.

2.2.2.3 Output Layer

The output layer includes:

- Seven output groups (One per frequency band).
- Each group contains five neurons corresponding to the five users.
- Activation function: Softmax

2.2.2.3.1 Softmax Activation Function

The probability that user i is assigned to band k is determined by the output activation function, Softmax. It is given by Equation (13):

$$S(\overrightarrow{Q})_i = \frac{e^{Qi}}{\sum_{l=1}^{K} e^{Qi}} \qquad (13)$$

where Q is the vector of real-valued outputs from the final dense.

2.2.3 Loss Function

To optimize the classification accuracy, the model minimizes the Categorical Cross-Entropy Loss given by Equation (14):

$$L(y,\hat{y}) = -\sum_{i=1}^{C} y_i \log(\hat{y_i}) \qquad (14)$$

where $L(y,\hat{y})$ = categorical cross-entropy loss, y_i= the true allocation (0 or 1 for each class), $\hat{y_i}$ = predicted probability for class i and C = number of classes.

Hyperparameters tuned for the Deep Neural Network model included:

i. Number of epochs = 100
ii. Number of batch size = 32
iii. Hidden layer 1 = 128 neurons
iv. Hidden layer 2 = 64 neurons
v. Optimizer = Adam
vi. Loss function = Categorical Cross-Entropy
vii. Activation (Hidden) = ReLU
viii. Activation (Output) = Softmax

The model was trained for 100 iterations (or episodes). This limit was selected because the system had successfully explored the search space and found optimal solutions without incurring needless computational costs by the time the performance metrics are stabilized.

2.2.4 Adaptive Multi-Objective Reward

The DNN optimizes a reward function that balances the conflicting objectives dynamically. To maximize spectrum efficiency while reducing interference, a penalty term is added to obtain Equation (15):

$$R_{eff} = \sum_{i=1}^{N}\left(\frac{T_i}{B_i} - \alpha I_i\right) \qquad (15)$$

where I_i = the interference level experienced by user i and α = a scalar penalty factor for interference impact. The efficiency bandwidth is rewarded by the term $\frac{T_i}{B_i}$, favoring higher throughput with minimal bandwidth consumption.

In addition to spectrum efficiency and throughput, noise level also adversely affects communication quality. Hence, a penalty for noise level was introduced with a dynamic adjustment based on performance metrics. This aims to help maintain optimal spectrum allocation over time and the adaptability reflect the system's response to variability conditions. Thus, the revised reward function is given by Equation (16):

$$R_m = \sum_{i=1}^{N} \left(\frac{T_i}{B_i} - \alpha I_i + \beta \left(\frac{1}{N_i} \right) \right) \tag{16}$$

where N_i = the noise level experienced by user i and β = a dynamic adjustment based on historical performance penalty factor. The term $+ \beta \left(\frac{1}{N_i} \right)$ = noise penalty. Thus, the higher the value of N_i, the lower the reward. The parameter β can be adjusted depending on the system's performance, allowing the reward to adapt to varying noise environment.

3 RESULTS FOR DNN IN TERMS OF PERFORMANCE METRICS AND SPECTRUM ALLOCATION

The Deep Neural Network (DNN) model was evaluated based on its ability to optimize the allocation of 7 spectrum bands among 5 users over 100 iterations (epochs). The model's performance was assessed using four key metrics, namely, Interference, Throughput, Spectral Efficiency, and Fairness.

3.1 Optimized Spectrum Allocation Matrix

The DNN model predicted the following optimal binary allocation matrix in Equation (17). A value of '1' indicates that a channel is assigned to a user, while '0' indicates no assigned channel. In this optimal configuration, User 5 (last row in Equation (17)) was not assigned any band to minimize system-wide interference. The multi-objective function prioritizes minimizing system-wide interference and optimizing overall spectral efficiency, which leads to this exclusion. Assigning a band to User 5 would disproportionately reduce the system's overall performance and raise interference for other users if their particular channel circumstances (sensed interference/noise) are noticeably worse than others.

$$Allocation_{DNN} = \begin{bmatrix} 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 1 & 1 \\ 1 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \tag{17}$$

Figures 2-5, display the performance metrics for Interference, Throughput, Spectral Efficiency and Fairness respectively.

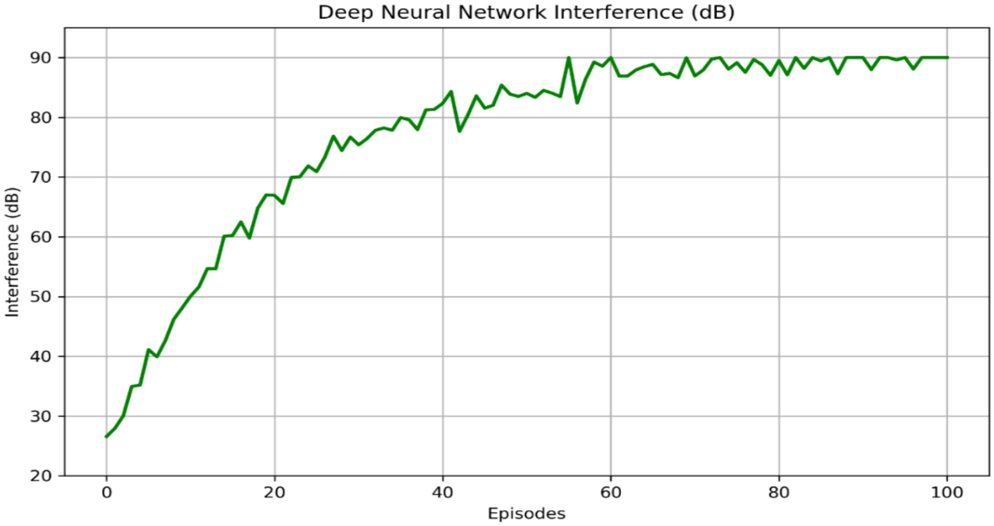

Figure 2: Interference for Deep Neural Network Model

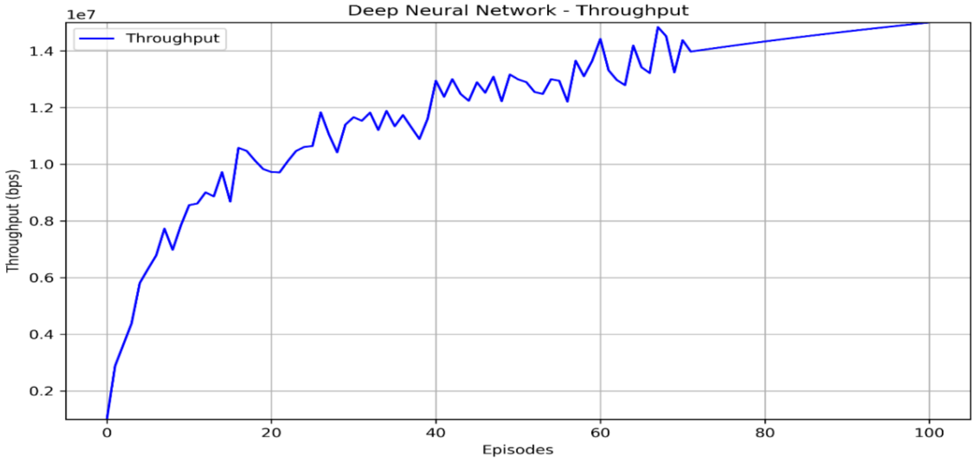

Figure 3: Throughput for Deep Neural Network Model

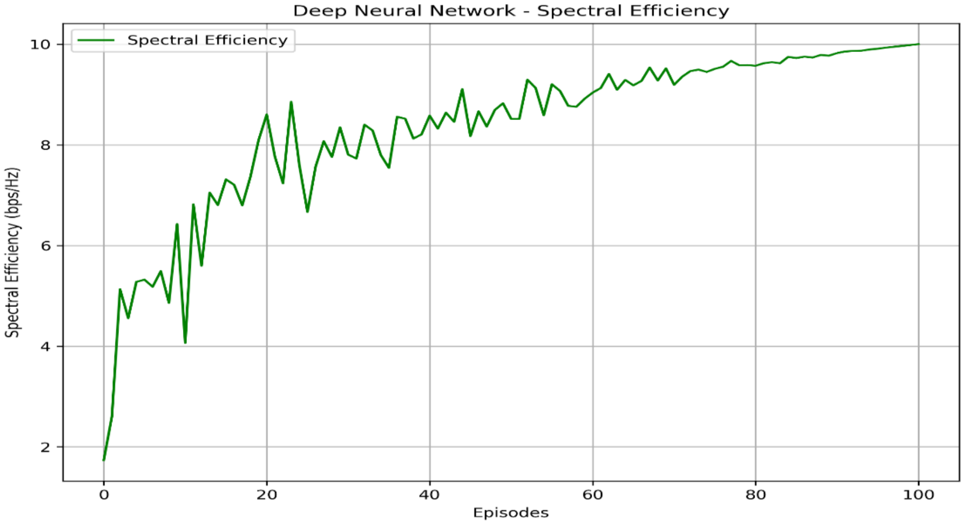

Figure 4: Spectral Efficiency for Deep Neural Network Model

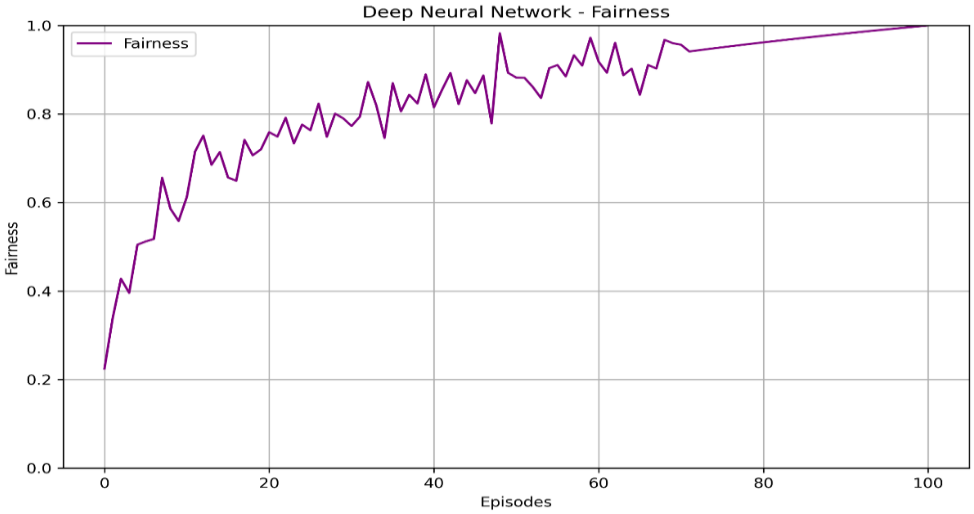

Figure 5: Fairness for Deep Neural Network Model

3.2.1 Discussion of Results

The results show that Deep Neural Network approach effectively maps intricate interference patterns to the best channel assignments by handling the spectrum allocation problem as a classification problem. In terms of Interference (dB), the DNN model achieved a steady minimization of interference, reaching an optimal value of 90 dB at the 65th iteration and maintaining this stability through the 100th iteration (as shown in Figure 2). The Throughput (bps) showed a steady rise, starting at 2.0 $*10^6$ bps and peaking at 1.5$*10^7$ bps by the 100th iteration (as shown in Figure 3). For Spectral Efficiency (bps/Hz), the model demonstrated exceptional efficiency, rising from 2 bps/Hz initially to a peak of 10 bps/Hz after the 72nd iteration (as shown in Figure 4). Finally, Fairness Index using the Jain's Fairness Index improved significantly from 0.22 to a near-perfect score of 0.99–1.00, indicating equitable resource distribution among the active users (as shown in Figure 5). The DNN proposed framework, is scalable by nature. The model can handle larger networks by varying the size of the input layer (which accepts an N x M feature vector) and the output layer. The inference time for real-time allocation stays small (sub-millisecond), making it appropriate for dynamic situations, even though increasing the number of users (N) or bands (M) increases the computing complexity during the training phase.

3.3 Validation of the DNN Result with Existing Works

The validation of the proposed DNN model with existing works in existing literature is shown in Table 1.

Table 1: Validation of Proposed DNN Model against Existing Works

Author	Technique Used	Metric of Comparison	Literature Result/ Present Study Result
[11]	Deep Neural Network (DNN)	Spectral Efficiency	~3.6 bps/Hz/10 bps/Hz

[10]	Deep Neural Network (DNN)	Average Spectral Efficiency	6.36 bps/Hz/10 bps/Hz
[12]	Hybrid Fuzzy Logic	Interference	69 dB/90 dB
[13]	Genetic Algorithm	Interference	24 dB/90 dB
[14]	Combined DNN with cooperative multi-agent systems and Q-learning.	Throughput	$1.43*10^6$ bps/$1.5*10^7$ bps
[15]	Convolution Neural Network (CNN)	Fairness Index	0.94/ 1.00

The proposed DNN model's performance was evaluated against existing state-of-the-art research, in order to confirm its robustness. Spectral Efficiency, Throughput, Fairness and Interference were the main metrics for the validation. From Table 1, it is seen that the proposed DNN model achieved the following:

(i.) **Superior Spectral Efficiency:** With a Spectral Efficiency of 10 bps/Hz, the proposed DNN model greatly outperformed the 3.6 bps/Hz and 6.36 bps/Hz reported by [11] and [10] respectively. The study's optimized Levenberg-Marquardt training algorithm is responsible for the improvement.
(ii.) **Maximized Throughput:** Compared to $1.43*10^6$ bps obtained by [14] in the hybrid system of DNN and Q-learning, the proposed model in this study had a superior throughput maximization for the same 5 users' scenario.
(iii.) **Enhanced Fairness:** The proposed model in this study outperformed the CNN model in [15] with a Fairness Index of about 1.00, guaranteeing that no user is deprived of resources.
(iv.) **Interference Reduction:** Compared to 24 dB attained by conventional Genetic Algorithms of [13] and the 69 dB by hybrid Fuzzy systems of [12], the proposed model's capacity to reduce interference to 90 dB is significantly better.

The results obtained compared with existing research ([11] and [10]) in Table 1 showed that the proposed DNN model's improved Spectral Efficiency (10 bps/Hz), this shows its architectural efficiency. Despite the possibility of slightly modified simulation parameters (user count, bandwidth) from the existing studies, these studies still represent the current performance ceiling for cognitive radio allocation.

CONCLUSION

This study has shown effectively how Deep Learning can be used to address the challenging issue of spectrum allocation in Television White Space (TVWS) particularly the Ultra-High Frequency (UHF) band. Through the use of a Deep Neural Network (DNN) that was trained using the Levenberg-Marquardt backpropagation algorithm, an adaptive framework was developed that can simultaneously optimize four competing goals: Interference, Throughput, Spectral Efficiency, and Fairness.

The DNN model provided a reliable option for next generation Cognitive Radio Networks, according to the simulation results. It greatly outperformed conventional heuristic techniques and other AI benchmarks, achieving a high Spectral Efficiency of 10 bps/Hz, Throughput of $1.5*10^7$ bps and a Fairness Index of 1.00. Additionally, the model successfully reduced interference to 90 dB, guaranteeing sustained cohabitation between primary and secondary users. In comparison to iterative search techniques, it is concluded that addressing spectrum allocation as a multi-classification problem enables faster, more equitable and highly efficient resource allocation. However, some limitations observed are: dependence on simulated and randomly generated data, limited system size of 5 users and 7 bands and lack of online learning. Future research can improve on the limitations encountered in this study by concentrating on testing the architecture against actual hardware testbeds and integrating this model with web frameworks (like FastAPI) for real-world deployment on edge devices, online adaptation mechanism and consideration of a large scale, real time cognitive radio network, thereby improving the robustness, scalability and practical feasibility of the proposed DNN model.

REFERENCES

[1] Chiwewe, T.M. (2016). Efficient spectrum use in cognitive radio networks using dynamic spectrum management. *Ph.D. University of Pretoria, South Africa.*

[2] Chiwewe, T. M. and Hancke, G. P. (2016). A Cognitive Radio Framework for the Industrial Internet of Things. *IEEE Transactions on Industrial Informatics*, 12(3), 1102-1111.

[3] Ibhaze, A.E., Orukpe, P.E. and Edeko, F.O. (2020). Li-Fi prospects in internet of things network. In: K. Arai et al. *(Eds), Advances in Information and Communication*, FICC 2020. Advances in Intelligent Systems and Computing, vol 1129. Springer, Cham, pp.272-280.

[4] Bello, N. and Muhammed, A.A. (2022). Effect of buffer size variation on video quality transmission in a cognitive radio network. *Journal of Civil and Environmental Systems Engineering, University of Benin*, 19(1), pp.34-39.

[5] Idubor, S. O., Noma-Osaghae E., Ogbeide K. O. and Okokpujie K. (2018). A step towards enhancing spectrum utilization by implementing a spectrum sensing cognitive radio using an RTL-SDR. *International Journal on Communications Antenna and Propagation*, 8(5), pp.439-447.

[6] Pineda, D. and Hernandez, C. (2019). Cognitive radio for TVWS usage. TELKOMNIKA (Telecommunication Computing Electronics and Control), 17(6), pp.2735-2746.

[7] Ufoaroh, S. U. and Abu, K., (2018). Assessment of TV white spaces availability in Southern Nigeria (A case study of Ugbowo, Benin City). *International Journal of Electrical and Telecommunication System Research*, 10(10), pp.22-32.

[8] Gayathri, N.H., Anandakumar, R.S., and Gowri, S. (2023). An Investigation on Spectrum Mobility Mechanisms in Cognitive Network Communication. *2023 9th International Conference on Advanced Computing and Communication Systems (ICACCS)*, Coimbatore, India, pp. 2433-2437

[9] Mach, J. B., Ronoh, K. K. and Langat, K. (2023). Improved spectrum allocation scheme for TV white space networks using a hybrid of firefly, genetic, and ant colony optimization algorithms. *Heliyon*, 9(3), e13921.

[10] Gupta, K. and Dhurandher, S.K. (2023). CASE: Channel allocation for optimized spectral efficiency using deep neural network in underlay cognitive radios. In: *2023 International Conference on Computer, Information and Telecommunication Systems (CITS)*. https://doi.org/10.1109/cits58301.2023.10188791.

[11] Lee, W. (2018). Resource allocation for multi-channel underlay cognitive radio network based on deep neural network. *IEEE Communications Letters*, 22(9), pp.1942-1945.

[12] Rajesh, G., Raajini, X. M., Sagayam, K.M., Bhushan, B. and Köse, U. (2020). Fuzzy genetic based dynamic spectrum allocation (FGDSA) approach for cognitive radio sensor networks. *Turkish Journal of Electrical Engineering & Computer Sciences*, 28(5), pp.2416-2432.

[13] El Rharras, A., Saber, M., Chehri, A., Saadane, R., Hakem, N. and Jeon, G. (2020). Optimization of spectrum utilization parameters in cognitive radio using genetic algorithm. *Procedia Computer Science*, 176, pp.2466-2475.

[14] Elhachmi, J. (2022). Distributed reinforcement learning for dynamic spectrum allocation in cognitive radio-based internet of things. *IET Networks*, 11(6), pp.207-220.

[15] Benerjee, V. and Rai, R. (2023). Resource Allocation in Cognitive Radio Networks based on Deep Learning Algorithm. *International Journal of Emerging Technologies and Innovative Research*, 10(12), pp.165-170.