European Journal of Science, Innovation and Technology
ISSN: 2786-4936
www.ejsit-journal.com
Volume 4 | Number 2 | 2024

An In-depth Investigation of AI-driven Dynamic Spectrum Allocation in Cellular Networks

S. M. Ekolama[1] and D. Ebregbe[2]
[1]Department of Agricultural and Environmental Engineering,
Faculty of Engineering,
Niger Delta University,
Wilberforce Island, Amassoma, Bayelsa, Nigeria
[2]Department of Electrical Engineering,
Faculty of Engineering,
Niger Delta University,
Wilberforce Island, Amassoma, Bayelsa, Nigeria

ABSTRACT
The study explored the use of artificial intelligence (AI) model for dynamic spectrum allocation in cellular networks. It aims to optimise spectrum allocation and address static issues by adaptively allocating frequency bands based on real-time demand. The research examines conventional methods of allocating spectrum and presents AI as a potential solution to spectrum shortage problems. Deep-Q algorithm was chosen to develop the model, which is built as a framework of components, system architecture, and methods that could be integrated into existing networks to facilitate dynamic spectrum allocation. This approach enhances real-time spectrum allocation and dynamic decision-making to adaptively assignment frequency. The model was evaluated for its throughput, spectrum efficiency of available spectrum management and other metrics in both simulated scenarios by representing various network topologies and traffic situations, as well as real-life network. It was observed that the model exhibits 88 percent efficiency in intelligently managing available spectrum. This shows that AI-driven dynamic spectrum allocation is far advantageous compared to conventional static allocation approach with limitations, and other factors. The achievement of 88 percent spectrum allocation through our AI-driven dynamic spectrum allocation, shows that the study contributed to the body of knowledge on cellular network management.

Keywords: Mobile, GSM, Call, Cellular Network, Gateway, Communication, Artificial Neural Network, GSM Operation, predictive maintenance

INTRODUCTION

The increasing demand of communication services introduced by mobile devices, Internet of Things, and innovative applications has led to a critical re-evaluation of traditional methods of spectrum allocation. As networks grow into complex ecosystem, problems of limited spectrum and static allocation constraints in dynamically developing networks become apparent. The traditional fixed spectrum assignment method cannot keep up with the changing demands of new applications and their dynamic communication patterns. This is what informed this research to examine how dynamic spectrum allocation driven by artificial intelligence (AI) can address the convergence of these issues and provide possible remedies. In order to improve spectrum usage in cellular networks, the study seeks to provide insights on the integration of AI technologies for adaptive and real-time spectrum allocation. The necessity for creative solution in effective spectrum management is emphasised by the limited nature of electromagnetic spectrum and the constraints of static allocation in a continuously changing cellular environment.

LITERATURE REVIEW

According to studies on spectrum allocation, conventional techniques such as frequency division multiple access (FDMA) and time division multiple access (TDMA) are not adaptable enough to satisfy the changing requirements of cellular networks (Sarker, 2021). A major component of traditional spectrum distribution is fixed spectrum allotment, which may result in congestion during periods of high demand and underutilization during periods of low demand. The drawbacks of fixed spectrum allocation become increasingly apparent as cellular networks grow to accommodate a wider variety of devices and applications (Elsayed & Erol-Kantarci, 2019). In order to tackle these problems, researchers and industry professionals are investigating dynamic spectrum allocation methods, which use artificial intelligence to assign frequencies according to usage trends, network circumstances, and current demand. This paper emphasises the need for smarter and flexible approaches in the ever evolving area of cellular communication.

Spectrum management has traditionally been based on fixed allocation approaches like TDMA and FDMA; however, these paradigms have been reevaluated due to their inability to adjust to the dynamic nature of cellular networks (Houssein et al., 2021). Dynamic spectrum access might be revolutionise by cognitive radio networks, which possess the ability to actively monitor and adapt to their radio frequency environment (Ahmad et al., 2020). The dynamic allocation method gains more intelligence and flexibility with the incorporation of artificial intelligence (AI) (Antonopoulos et al., 2020). This is why this paper explores the use of AI-driven dynamic spectrum allocation in cellular networks with the goal of bridging the gap between AI technology and cognitive radio concepts. It seeks to shed light on the revolutionary potential of AI-driven solutions as well as how they may affect spectrum usage and the development of cellular networks in the future.

Intelligent and adaptive spectrum management systems have become imperative as a result of the growing demand for communication services and frequency scarcity (Qamar et al., 2020). Thus, artificial intelligence (AI) can be used for spectrum allocation to enhance network flexibility, adaptability, and efficiency (Yang et al., 2020). AI-driven spectrum allocation uses machine learning, deep learning, and reinforcement learning techniques to enable networks to self-adapt to changing conditions (Bhattacharyya et al., 2023). Neural networks, decision trees, and support vector machines are a few types of machine learning techniques (Hamad, 2020). As cellular networks adjust to new applications like autonomous vehicles and smart cities, adaptive spectrum distribution becomes more important (Nassar & Yilmaz, 2021).

Artificial Intelligence (AI) models can be used in dynamic spectrum allocation systems as a result of the proliferation of cellular communication services (Kaur & Kumar, 2022). Through the application of machine learning, deep learning, and reinforcement learning methods, AI-driven spectrum allocation can enable autonomous decision-making in real-time (Feriani & Hossain, 2021), enabling cellular networks to optimise frequency band allocation and adapt to changing circumstances (Huang et al., 2020). This strategy can completely change how cellular networks handle frequency resources (Kebede et al., 2022). AI-driven spectrum allocation heavily relies on deep learning model (Sheth et al., 2020), which enable the model to make well-informed judgements based on inputs from real-life data (Dhabliya et al., 2023). This interaction is a major step forward in the search for cellular networks that are more adaptive and efficient.

Intelligent and adaptive approaches are becoming more and more popular due to the constraints of static spectrum allocation and the growing demand for cellular communication services (Rony et al., 2021). Networks can swiftly adapt to changing conditions thanks to artificial intelligence (AI), which makes dynamic spectrum allocation possible (Yang et al., 2020). The study on AI-driven spectrum allocation, emphasis how AI can enhance efficiency, lessen interference, and resolve problems in cellular networks (Chataut et al., 2024). It suggests reinforcement learning as a major player in AI-driven algorithm, enabling agents to make decisions in response to changing demands and environmental conditions (Soori, Arezoo, & Dastres, 2023). This ensures that by using AI-driven solutions, cellular communication networks of the future will be more intelligently efficient.

MATERIALS AND METHODS

Model Framework Design

A dynamic spectrum allocation system powered by AI is the goal of this research, with an emphasis on efficiency, flexibility, and real-time decision-making. To achieve this goal, a framework was designed and structured into three: Perception Layer, Decision Layer, and Execution Layer.

Using cutting-edge methods like cognitive radio sensing and reinforcement learning-based algorithmic spectrum analysis, the Perception Layer gathers real-time spectrum sensing data on network characteristics. Using this method, it continuously monitors the radio frequency in the environment, and passes this information to the decision layer. The decision layer analyses these data and make dynamic judgements with respect to available spectrum and the demands from several devices and pass the information to the execution layer. Using reinforcement learning algorithms, the execution layer allocates frequency in a dynamic and intelligent manner, maximizing the available frequency bands. With reward-based dynamic decision-making approach, the algorithm gradually learns and adjust to changing network circumstances. This process optimises frequency band allocation in response to demand in real time, adapting to erratic network circumstances.

This modular layer design guarantees a reliable and expandable cellular network solution. And provides a dynamic and adaptive solution to spectrum shortage concerns by gathering, deciding, and executing spectrum allocation intelligently.

The framework provides an overlay for cellular network by laying the groundwork for integration with existing network infrastructure.

By acting as an overlay to the national regulatory authority as shown in Figure 1, the framework makes it easier for the system to communicate with other elements of the network. This eliminates the need for a whole rebuild of operator's infrastructure and enables the framework to make use of legacy systems, integrate real-time data from existing networks, and provide adaptive spectrum allocation.

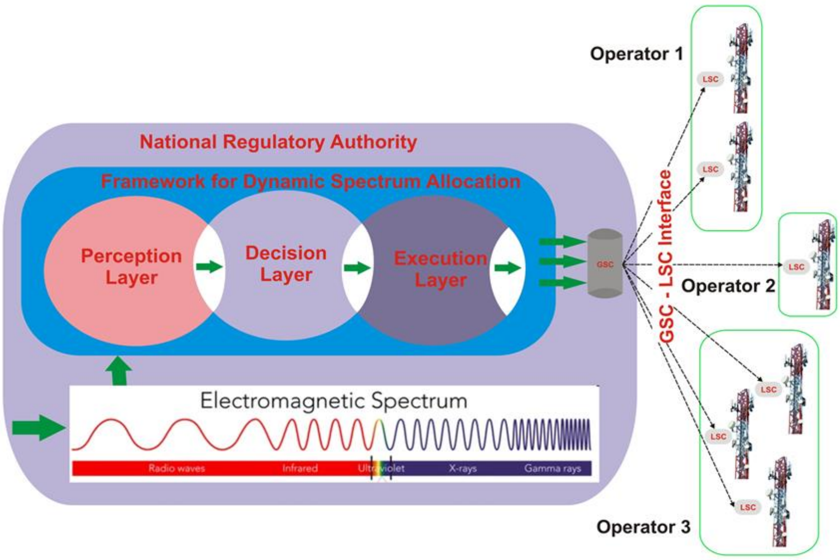

Figure 1. Framework for intelligent spectrum allocation in cellular network

The AI-driven dynamic spectrum allocation framework is a system that leverages reinforcement learning algorithms and cognitive radio sensing to identify possibilities and difficulties in real-time. Once the data is received by the Decision Layer, the model analyse it to extract useful information. Because the framework makes decisions based on past learning and the present spectrum condition, it adjusts and improve allocation process over time. Based on the current needs of the cellular network, the framework dynamically modifies frequency allocations with respect to real-time spectrum sensing methods like feature extraction and pattern recognition. The system haven perceives and analyse the network environment in real-time, it makes intelligent, context-aware judgement about spectrum allocation because of the strong synergy between spectrum sensing and decision-making processes.

Model Design

We took a stepwise approach to design the algorithm of the model for the dynamic spectrum allocation as follows:

i. Define Objectives and Requirements

We started the design with a clear definition of the objectives which include: maximizing spectrum utilization, minimizing interference, optimizing Quality of Service (QoS), and supporting dynamic spectrum sharing. We also identify specific requirements and constraints such as regulatory policies, spectrum availability, user priorities, network topology, and technology compatibility. These factors guided the design and implementation of the model.

ii. Data Collection and Preprocessing

The established objectives and requirements gave rise to collection and preprocessing of data for the dynamic spectrum allocation model. This involved gathering historical and real-time data on spectrum usage, traffic patterns, user preferences, environmental conditions, and interference levels. The collected data was then preprocessed to remove noise, handle missing values, normalize features, and was used to prepare the dataset for training the model, ensuring the quality and accuracy of the input data.

iii. Feature Selection and Engineering

We identified, selected and engineered the relevant features influencing spectrum allocation for correct decision making for the model. These features include user location, application type, network load, channel conditions, and spectrum availability. Feature engineering techniques were applied to extract meaningful data to create new features in place of missing ones, and enhance the efficiency of the model, to enable accurate and effective spectrum allocation management.

iv. Choosing Algorithm for the Model

Deep-Q algorithm was chosen for the development of the model. The choice was influenced due to the capability of Deep-Q algorithms to learning from data, make intelligent decisions, and dynamically adapt to changing spectrum conditions and user requirements, ensuring optimal spectrum allocation performance in network environment as shown in Figure 2.

v. Training, Testing, and Validation

The model was trained using the prepared dataset, and was validation to optimize the model performance and ensure accuracy, generalization ability, and robustness. Simulated testbed experiments were conducted to evaluate the model's performance under various scenarios, including different traffic loads, mobility patterns, interference scenarios, and spectrum availability conditions. Key performance metrics include spectrum efficiency, throughput, latency, fair share of resources, and interference mitigation were measured to assess the model's capability to perform optimally under any condition.

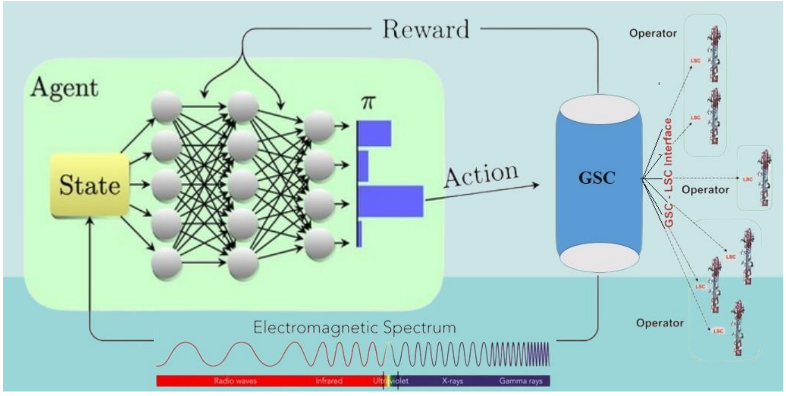

Figure 2. Deep-Q Learning Model for Dynamic Spectrum Allocation in a Cellular Network

Deployment and Integration

The model was optimized based on simulated data which enabled the fine-tuning of its parameters to improve its decision-making capability and enhance its spectrum allocation efficiency, adaptability, and scalability. After the optimization, the model was deployed and integrated into real-life cellular network infrastructure to monitor its performance metrics, and dynamic changes in both urban and rural conditions in comparison to existing process presented in the work of Dalla Pozza et al. (2022) shown in Figure 3.

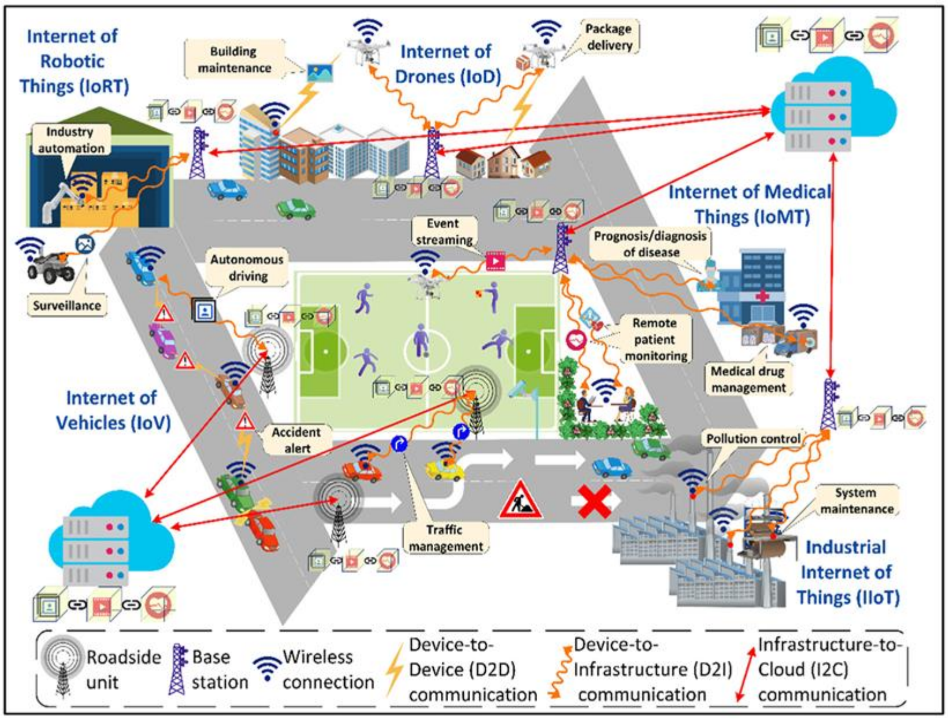

Figure 3. Dynamic Spectrum Allocation
Source: Dalla Pozza et al. (2022)

Figure 3 shows a typical scenario of devices demand of spectrum allocations, which formed the bases of validating the effectiveness of the model by comparing it to traditional static allocation techniques, with a focus on reducing interference, responding to changing network circumstances, and efficiency of spectrum allocation in both urban and rural locations.

RESULTS AND DISCUSSION

Table 1 shows a dataset from the integration of data from existing database and data from the simulated network.

Table 1. Consolidated Data from Simulated and Existing Database

Application Type	Network Load (%)	Spectrum Availability (MHz)	…	Device Type
Video Streaming	55	92	…	Smartphone
Voice Call	28	74	…	Feature Phone
Data Transfer	74	46	…	Laptop
Gaming	37	110	…	Console
Drone Sensors	18	64	…	IoT Device
Teleconferencing	64	83	…	Tablet
Social Media	46	69	…	Smartphone
Auto Navigation	9	138	…	GPS Device
GPS Tracking	14	60	…	Laptop
…	…	…	…	…
Music Streaming	23	101	…	Sensor Device

The consolidated table was used to produce a dataset. The dataset was split into three: training set, testing set, and validation set for training of the model. After the training, the model was deployed and used for allocation of spectrum based on application type, network load, available spectrum and demands from devices, as show in the graph of Figure 4.

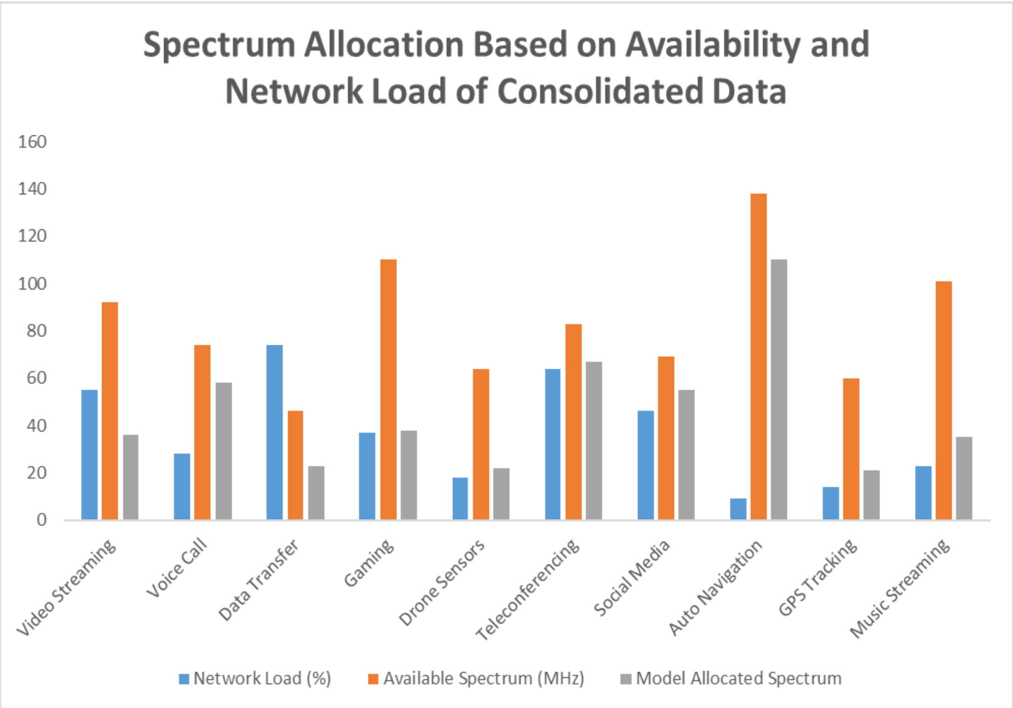

Figure 4. Graph of Model Allocated Spectrum using integrated Dataset

As seen above, Table 1 is an integration of existing (historical) data with simulated data. To obtain the simulated data, GNS3 VMware Workstation was used to setup the virtual network testbed. In the simulation, the core cellular network architecture, as well as the respective device components were presented as shown in Figure 5.

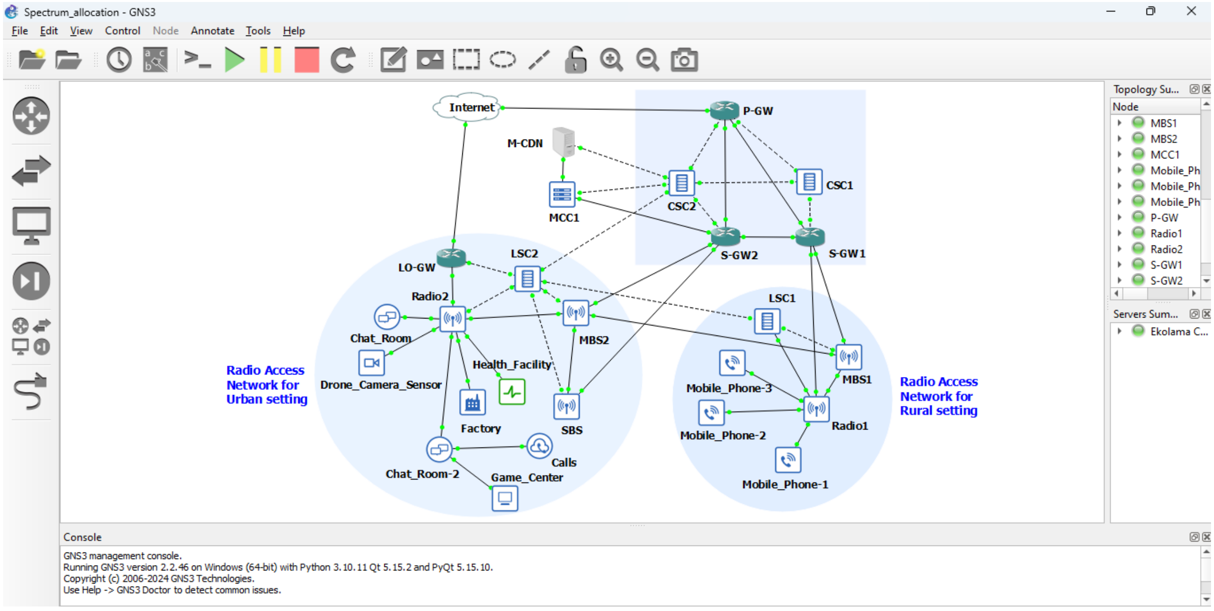

Figure 5. Virtual Network for Experimental Test-Bed

The network topology from the GNS3 simulator was exported to Gephi for visualization and graphing, ensuring that it reflects the network setup and established connections to be visualized in Gephi. This enabled the capture of network traffic, data flow and interactions among devices in the topology, as shown in Figure 6.

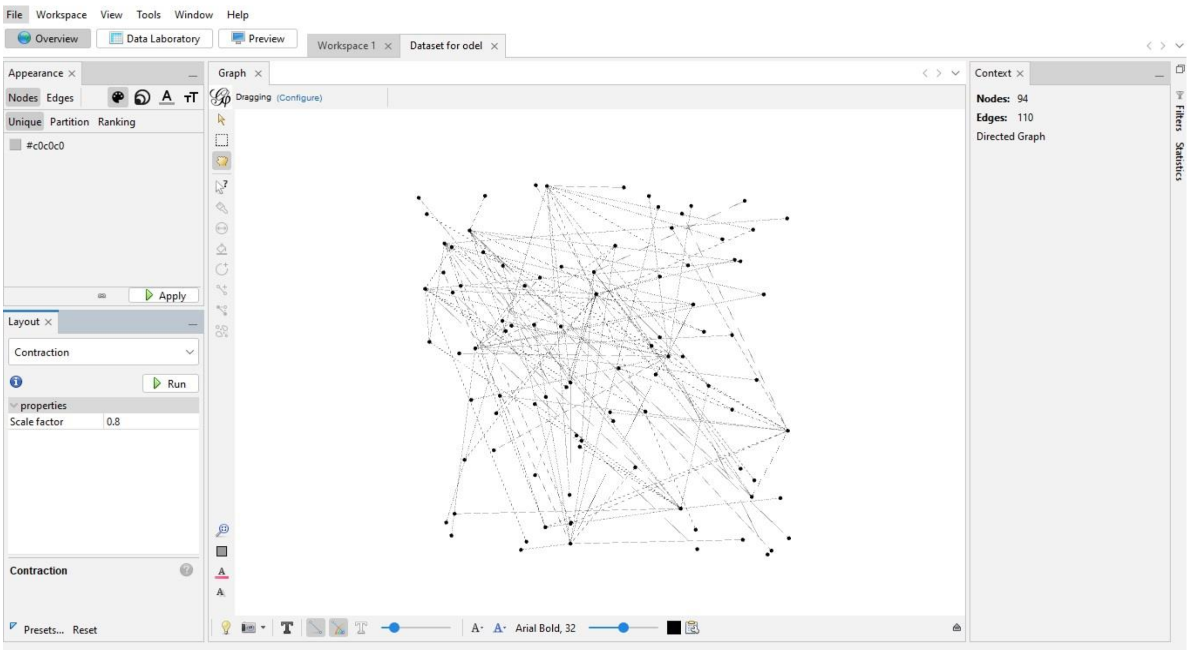

Figure 6. Visualization of Network Density and Allocation of Available Spectrum Using Gephi

The data from Gephi was tabulated to give the simulated dataset as shown in Table 2.

Table 2. Data from Simulated Network

Application Type	Network Load (%)	Spectrum Availability (MHz)	…	Device Type
Video Streaming	65	108	…	Smartphone
Voice Call	32	86	…	Feature Phone
Data Transfer	86	54	…	Laptop
Gaming	43	130	…	Console
Drone Sensors	22	76	…	IoT Device
Teleconferencing	76	97	…	Tablet
Social Media	54	81	…	Smartphone
Auto Navigation	11	162	…	GPS Device
GPS Tracking	16	70	…	Laptop
…	…	…	…	…
Music Streaming	27	119	…	Sensor Device

The dataset of the simulated data was supplied as input to the model, and was used to allocate available data, as shown in Figure 7.

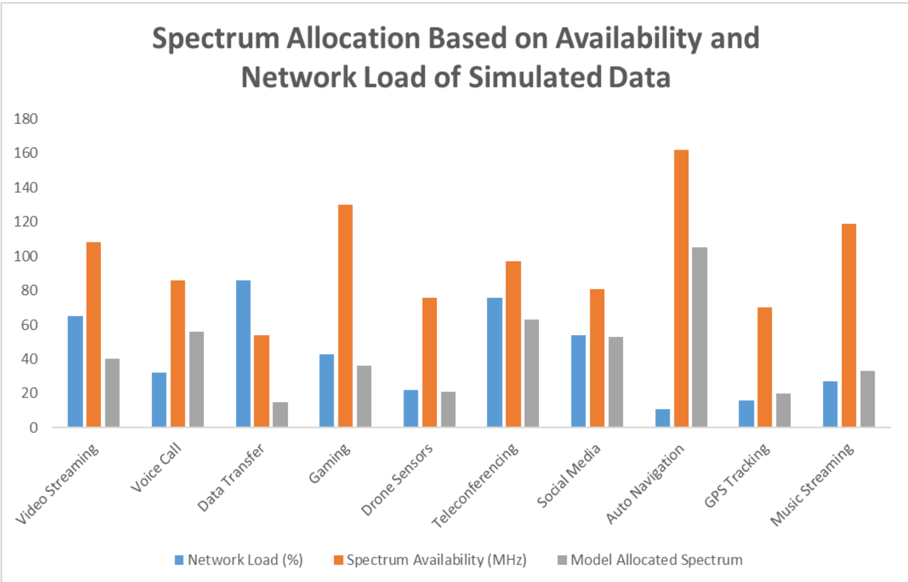

Figure 7. Graph of Model Allocated Spectrum using Simulated Dataset

The data gathered from existing database was tabulated to give the existing (historical) dataset as shown in Table 3.

Table 3. Existing (historical) Database

Application Type	Network Load (%)	Spectrum Availability (MHz)	…	Device Type
Video Streaming	60	100	…	Smartphone
Voice Call	30	80	…	Feature Phone
Data Transfer	80	50	…	Laptop
Gaming	40	120	…	Console
Drone Sensors	20	70	…	IoT Device
Teleconferencing	70	90	…	Tablet
Social Media	50	75	…	Smartphone

Auto Navigation	10	150	…	GPS Device
GPS Tracking	15	65	…	Laptop
…	…	…	…	…
Music Streaming	25	110	…	Sensor Device

The historical dataset was supplied as input to the model, and was used to allocate available spectrum, as shown in Figure 8.

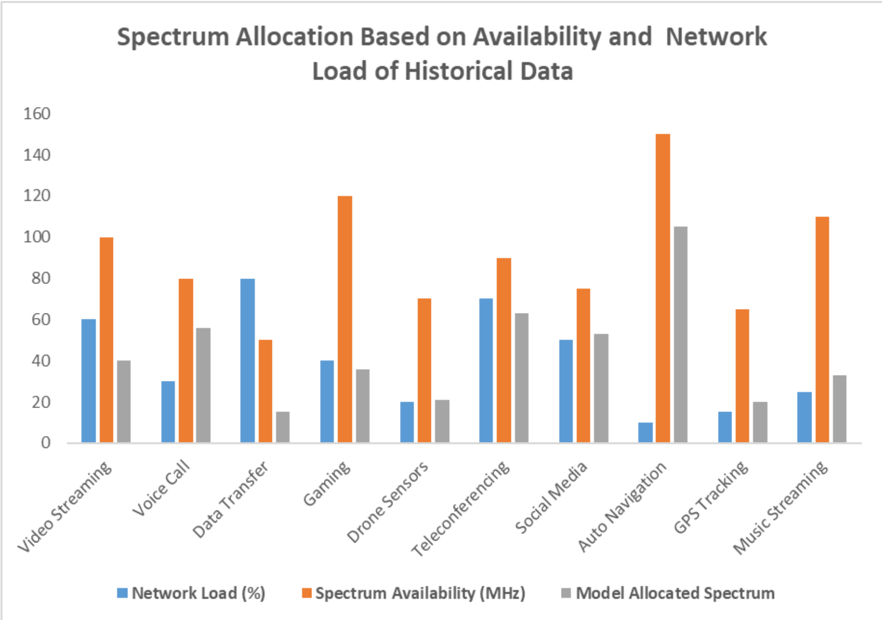

Figure 8. Graph of Model Allocated Spectrum using existing Dataset

The model was validated using the two datasets: simulated and existing dataset, as well as the integration of both. The model proved to effectively manage available spectrum up to 88 percent efficiency as shown in Figure 9.

```
Table Head
         Latitude        Longitude Application Type  Network Load (%)  \
0    187.125.25.83   192.168.200.88              SDP              5005
1  190.168.102.254    192.168.102.9              SIP                23
2   208.158.55.119   192.168.44.169             RTCP              1720
3    166.255.80.63  192.168.152.192              SIP               162
4   187.125.151.92  192.168.153.107              RTP                25

  Channel Conditions (Good, Fair, Poor)  Spectrum Availability (MHz)  \
0                                   552                          623
1                                   477                         2691
2                                   172                         1657
3                                   238                         3077
4                                   287                         3441

     User Priority
0  Buffer Overflow
1           Normal
2         Zero Day
3         Zero Day
4            Probe

 Dynamic Spectrum Allocation
 Accuracy: 0.8833333333333333
```

Figure 9. Result of Efficient Management Test of the Model

CHALLENGES AND FUTURE DIRECTION

While highlighting the possibilities of AI-driven dynamic spectrum allocation, the research also draws attention to its drawbacks. Complex cellular settings need precise modelling, and the quality and variety of training data determine how successful AI models will be. Continuous refining is necessary since incomplete or biased datasets might result in poor performance. Future studies should focus on reducing these difficulties, expanding the utilization of AI technologies, promoting collaboration among academic institutions, business associations, and government agencies, and exploring the integration of AI with cutting-edge technologies such as edge computing, 6G networks, and quantum communication.

The study on the use of AI in cellular network spectrum allocation is important since it takes into account new risks, such as adversarial attacks, that might jeopardise the accuracy of judgements. Creating strong models to identify and reduce security risks is crucial for ensuring the stability of AI-driven frameworks. Users' privacy is another issue as well, since AI algorithms examine private data. A combination of strict data security measures and privacy is needed to strike a compromise between optimising spectrum allocation and protecting user privacy. Future directions for AI-driven dynamic spectrum allocation should place an emphasis on privacy- and security-aware systems that use federated learning strategies, secure multi-party computing, and cutting-edge encryption.

It implies that, in order to manage dynamic and diverse cellular settings, more advanced AI models are required. In order to increase adaptability and predictive power, future research should concentrate on optimising machine learning algorithms, incorporating sophisticated neural network architectures, and using reinforcement learning approaches. It is also critical to address scalability issues in large-scale implementation. In the future, block-chain technology and AI model combination should be explored to increase security and transparency.

CONCLUSION

The use of AI-driven dynamic spectrum allocation in cellular networks was examined in this paper. The result showed a high level of reliance on the model to effectively manage available spectrum and resolve issues of spectrum allocation in contemporary cellular networks.

The study demonstrates that in dynamic network settings, the model performs better than conventional static approaches by minimising interference, guaranteeing equitable resource allocation, and adjusting to variety of network conditions, especially in crowded metropolitan settings where interference and spectrum shortages are frequent occurrences.

The model’s capacity to respond in real-time to changes in demand and reduce interference, position it for dynamic and congested network environment such as urban area which poses challenges for traditional static allocation approaches, which result in less-than-ideal spectrum resource management.

Consequently, in a metropolitan context with a wide range of communication demands, the AI-driven approach provides equitable access to spectrum resources allocation while improving overall performance, addressing specific difficulties, reducing latency, and ensuring fairness in resource distribution, which enhances network management by allowing networks to adapt to changing needs from users and applications.

The study also showed that in rural setting with low communication needs and low population density, the model still responds positively to spectrum allocation based on demand metrics. Which demonstrates that, even in situations where there are few connections, the model is flexible and efficient in allocating spectrum compared to traditional static allocation approaches which overcommit resources and are less flexible in responding to low resource demands of rural setting.

With 88% management efficiency, the model can be relied on in handling network issues of spectrum allocation. Consequently, the model satisfies various connection needs, low-latency communications, and data transfer speeds, all of which are in line with 5G and beyond goals, making the model to be a vital tool for the present and future network infrastructure need.

REFERENCES

Ahmad, W. S. H. M. W., Radzi, N. A. M., Samidi, F. S., Ismail, A., Abdullah, F., Jamaludin, M. Z., & Zakaria, M. (2020). 5G technology: Towards dynamic spectrum sharing using cognitive radio networks. *IEEE access, 8*, 14460-14488.

Antonopoulos, I., Robu, V., Couraud, B., Kirli, D., Norbu, S., Kiprakis, A., ... & Wattam, S. (2020). Artificial intelligence and machine learning approaches to energy demand-side response: A systematic review. *Renewable and Sustainable Energy Reviews, 130*, 109899.

Bhattacharyya, A., Nambiar, S. M., Ojha, R., Gyaneshwar, A., Chadha, U., & Srinivasan, K. (2023). Machine Learning and Deep Learning powered satellite communications: Enabling technologies, applications, open challenges, and future research directions. *International Journal of Satellite Communications and Networking, 41*(6), 539-588.

Chataut, R., Nankya, M., & Akl, R. (2024). 6G Networks and the AI Revolution—Exploring Technologies, Applications, and Emerging Challenges. *Sensors, 24*(6), 1888.

Dalla Pozza, N., Buffoni, L., Martina, S., & Caruso, F. (2022). Quantum reinforcement learning: the maze problem. *Quantum Machine Intelligence, 4*(1), 11.

Dhabliya, D., Al–Jawahry, H. M., Sharma, V., Jayadurga, R., & Jasmin, M. (2023, December). Long Short-Term Memory (LSTM) Networks for Stock Market Prediction. In *2023 4th International Conference on Computation, Automation and Knowledge Management (ICCAKM)* (pp. 01-07). IEEE.

Elsayed, M., & Erol-Kantarci, M. (2019). AI-enabled future wireless networks: Challenges, opportunities, and open issues. *IEEE Vehicular Technology Magazine, 14*(3), 70-77.

Feriani, A., & Hossain, E. (2021). Single and multi-agent deep reinforcement learning for AI-enabled wireless networks: A tutorial. *IEEE Communications Surveys & Tutorials, 23*(2), 1226-1252.

Hamad, R. (2020). An assessment of artificial neural networks, support vector machines and decision trees for land cover classification using sentinel-2A data. *Sciences, 8*(6), 459-464.

Houssein, E. H., Gad, A. G., Hussain, K., & Suganthan, P. N. (2021). Major advances in particle swarm optimization: theory, analysis, and application. *Swarm and Evolutionary Computation, 63*, 100868.

Huang, C., Hu, S., Alexandropoulos, G. C., Zappone, A., Yuen, C., Zhang, R., ... & Debbah, M. (2020). Holographic MIMO surfaces for 6G wireless networks: Opportunities, challenges, and trends. *IEEE wireless communications, 27*(5), 118-125.

Kaur, A., & Kumar, K. (2022). A comprehensive survey on machine learning approaches for dynamic spectrum access in cognitive radio networks. *Journal of Experimental & Theoretical Artificial Intelligence, 34*(1), 1-40.

Kebede, T., Wondie, Y., Steinbrunn, J., Kassa, H. B., & Kornegay, K. T. (2022). Multi-carrier waveforms and multiple access strategies in wireless networks: performance, applications, and challenges. *IEEE Access, 10*, 21120-21140.

Nassar, A., & Yilmaz, Y. (2021). Deep reinforcement learning for adaptive network slicing in 5G for intelligent vehicular systems and smart cities. *IEEE Internet of Things Journal, 9*(1), 222-235.

Qamar, F., Siddiqui, M. U. A., Hindia, M. N., Hassan, R., & Nguyen, Q. N. (2020). Issues, challenges, and research trends in spectrum management: A comprehensive overview and new vision for designing 6G networks. *Electronics, 9*(9), 1416.

Rony, R. I., Lopez-Aguilera, E., & Garcia-Villegas, E. (2021). Dynamic spectrum allocation following machine learning-based traffic predictions in 5G. *IEEE access, 9,* 143458-143472.

Sarker, I. H. (2021). Data science and analytics: an overview from data-driven smart computing, decision-making and applications perspective. *SN Computer Science, 2*(5), 377.

Sheth, K., Patel, K., Shah, H., Tanwar, S., Gupta, R., & Kumar, N. (2020). A taxonomy of AI techniques for 6G communication networks. *Computer communications, 161*, 279-303.

Soori, M., Arezoo, B., & Dastres, R. (2023). Artificial intelligence, machine learning and deep learning in advanced robotics, a review. *Cognitive Robotics, 3,* 54-70.

Yang, H., Alphones, A., Xiong, Z., Niyato, D., Zhao, J., & Wu, K. (2020). Artificial-intelligence-enabled intelligent 6G networks. *IEEE network, 34*(6), 272-280.

Solomon Malcolm Ekolama holds a Bachelor of Technology (B.Tech.) in Agricultural Engineering from Rivers State University of Science and Technology, (Now Rivers State University, Port Harcourt); Post Graduate Diploma (PGD) in Electrical Engineering (Electronics Option), from Rivers State University of Science and Technology, (Now Rivers State University, Port Harcourt); Master Degree in Electrical Engineering (Communications Option) from Rivers State University, Port Harcourt. He is currently a Doctoral Research Student in Electrical Engineering (Communication Option), Department of Electrical Engineering at the River State University, Port Harcourt. He is a Registered Engineer with the Council for the Regulation of Engineering in Nigeria (COREN); and an active member of several professional bodies, including: Nigerian Society of Engineers (NSE), Institute of Electrical and Electronics Engineers (IEEE), Nigerian Institution of Electrical and Electronics Engineers (NIEEE) and International Association of Engineers (IAENG). Ekolama has published in several reputable journals, which are featured in both Google Scholar and Research Gate. He is presently at the Department of Agricultural and Environmental Engineering, Niger Delta University, Wilberforce Island, Bayelsa State, Nigeria.

David Ebregbe was born in 1963. Snr. Lecturer, Department of Electrical and Electronic Engineering, Niger Delta University, Wilberforce Island, Bayelsa State, Nigeria. He holds a Bachelor of Engineering (B.Eng) degree in Electrical and Electronic Engineering from the University of Port Harcourt, Nigeria – (1987). Master of Science (M.Sc) in Digital Communications system from Loughborough University. United Kingdom (2002). Doctor of Philosophy (Ph.D) in Communications and Information Engineering, Harbin Institute of technology, Harbin, China – (2014). His research interests include; Radar, Mobile and wireless Communication, Statistical and Array signal processing.