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Novel Intelligent Sector-Based Approach for Congestion and Interference-Aware Load Balancing In 5G Heterogeneous Networks

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Abstract

Over the years, the unpredictable nature of user activities and traffic patterns has often caused overload and poor overall quality of service in 5G networks. The aim of this paper is a novel intelligent sector-based approach for congestion and interference-aware load balancing in 5G Heterogeneous Networks (HetNet). The research gap is the lack of an improved sector-based approach with congestion and interference awareness. The methodology used is experimental and simulation. The research design began with data collection of 5G HetNet traffic information from MTN Nigeria. The 5G network considered is HetNet with three cells, which are macro, micro, and pico. The area considered is Enugu Sub-urban. The joint congestion and interference problem was mathematically formulated as a non convex mix integer non-linear programming problem. The collected data were processed, and then applied to train five Machine Learning (ML) models (Multi-Layer Perceptron (MLP), Random Forest (RF), Support Vector Machine (SVM), Extreme Gradient Boosting (XGB), and Logistic Regression (LR)). To validate the models, five Deep Learning (DL) models (Convolutional Neural Network (CNN), Long Short Term Memory (LSTM), CNN+LSTM, Gated Recurrent Unit (GRU) and Bi-directional GRU (Bi-GRU)) were also trained and there results all compared considering metrics such as Coefficient of Determination (R2), Mean Square Error (MSE), and Root Mean Square Error (RMSE)). From the results, the XGB recorded the best performance with MSE of 0.0008, RMSE of 0.0291 and R^2 of 0.9966. Sector-based control was proposed using Clear Channel Assessment (CCA) and Carrier Annulling Algorithm (CAA). The intelligent traffic prediction model was applied to improve the proposed sector based for load balancing. The CAA utilized signal to noise ratio to sense interference in the channels while CCA was applied to avoid resource allocation to busy channel. Collectively these models were integrated to curate the novel intelligent sector-based congestion and interference-aware solution for 5G HetNet. In this paper, we call it the Intelligent Sector Based (ISB). The ISB was integrated on the 5G HetNet and simulated and compared against the benchmark Static Sector Based (SSB). The results reported 31.5% improvements for congestion management against the SSB, and also 55.9% noise reduction when compared to SSB. More simulations were done considering different user activities which include live streaming, phone calls, and file transfer. The results obtained showed consistent network performance success with ISB. Existing recent models in the literature like Proportional Fair (PF) and Deep Reinforcement Learning (Deep RL) were also compared with the ISB and ISS. The results obtained revealed

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that the model competes closely with the best which is Deep RL; however, the ISB is the best model which has the capacity to control both congestion and interference with a 5.905% improvement against Deep RL considering signal-to-noise ratio. In conclusion, this ISB is recommended for congestion and interference management in 5G HetNet.

Keywords: *Load Balance, Interference, Congestion, Machine Learning, Deep Learning, 5G HetNet.*

1. INTRODUCTION

The Fifth Generation (5G) mobile network became a main focus of research interest in the last few years. The network emergence promises improved global mobility management since a large number of spectrum sharing schemes is adopted to improve data traffic (Kadhim et al., 2023). This trend began with the deployment of Heterogeneous Network (HetNet). HetNet are made of macro cells and several sizes of small cells which include femto, pico, and micro. The key roles of these network cells are to collectively manage network traffic, extend 5G coverage, and improve the sustainability of 5G network (Wang et al., 2021). Thus, there is a high possibility that small cells may take over future networks, due to several advantages which include low economic implementation cost, limited space requirements, low energy consumption, and load balancing.

Due to increased traffic, improper deployment plan, dynamic user mobility patterns, 5G HetNet faces several issues, including interference (Onogwu et al., 2025), cyber attacks (Ifeanyi and Abonyi, 2025), poor performance index, congestion due to improper load balancing (Nwadike et al., 2024), and presents an urgent need for optimization. While these challenges have been addressed in the literature (Asadi et al., 2014), Kadhim et al. (2023) and Nwadike et al. (2024) argued that load balancing issue has not been decisively dealt with in 5G HetNet.

Load balancing (LB) is the balanced distribution of carried resources from user equipment within a HetNet for optimal service quality. Nwadike et al. (2024) define it as an optimization solution to traffic mis-match between user and cells within HetNet. Several approaches such as least connected algorithms (Han et al., 20217), A Hybrid of Monte Carlo's Algorithm (MCA) and Load Leveling Algorithm (LLA) (Usman et al., 2018), Machine Learning (ML) (Malekzadeh, 2023), optimization (Li et al., 2020), and gravitational search (Kavitha et al., 2020). However, despite the success of these models, the impact of adjacent interference and congestion in the channels remains unsolved.

Recently, ML techniques and Deep Learning (DL) have continued to gain massive research attention. Studies (Gures et al., 2022; Chabira et al., 2025; Nwadike et al., 2024; Anand et al., 2023; Ramesh et al., 2026) all applied ML to solve the congestion and interference problem in 5G network through load balancing. Similarly, literatures (El-Boudani et al., 2020; Ochoa et al., 2025; Zamzami, 2023; Nasser and Alani, 2025 and Zheng et al., 2022) all applied DL for the management of congestion and interference in 5G network. However, there are limited studies considered sector based approach to congestion and interference management problem. While the sector-based approach is not new, limited studies have improved it using clear channel assessment algorithm and channel nulling techniques. Secondly, while existing studies used ML and DL for network traffic prediction, there is need for extensive comparative analysis of several ML and DL model for short-term prediction that directly triggers the sector based load distribution model. Finally, there is insufficient attention to the simultaneous impact of interference during load balancing and handover distribution. To solve these issues, the following research questions are presented to be addressed.

i. How can ML and DL models be utilized effectively to predict in real-time 5G network traffic to support intelligent load balancing?

ii. To what extend can interference and congestion be managed during load balancing in 5G HetNet?

To answer these research questions, this paper propose novel intelligent sector-based approach for congestion and interference-aware load balancing in 5G heterogeneous networks. To achieve this aim, the following contributions are made in this paper.

i. Develop a novel mathematical formulation of joint interference and congestion problem as a non convex mixed integer nonlinear programming model

ii. We proposed and experimentally investigate ten advanced predictive models which include five classical ML and five DL architectures for accurate prediction of congestion in 5G HetNet.

iii. Present novel intelligent sector-based congestion and interference aware model for 5G HetNet.

iv. Present a novel sector based intelligent congestion and interference aware model using the prediction model, clear channel assessment technique, and channel nulling technique.

v. Carryout experimental simulations considering different files types, varying load and also benchmark against existing congestion control models.

2. LITERATURE REVIEW

The review of related paper will take a systematic approach, focusing on recent papers not less than 2020 considering ML and DL techniques on 5G quality of service optimization.

2.1 Related works on 5G service quality optimization using ML techniques

Congestion and interference are among the top issues threatening quality of service in 5G HetNet. Congestion occurs when the volume of data request exceeds network capacity (Khan et al., 2022), while Onogwu et al. (2025) define interference as a phenomenon that occurs when an external signal corrupts data transmission between a 5G network device and the cell tower. To solve this problem, several studies have proposed ML solutions. For instance, a comprehensive literature review was presented in Gures et al. (2022) to improve future HetNet using ML. In the study, LB was identified as a genetic problem. To solve the problem, literature on ML-based traffic distribution in dense HetNet were presented. The findings suggest that ML has great potential to detect potential congestion and interference problems in real time; however, DL is better because it extends the performance of classical ML, and it can trigger mobility robust optimization algorithms to help management the problem. In a similar fashion, Deep Reinforcement Learning (DRL) was fronted by Alwarafy et al. (2022) as a solution to radio resource allocation and management problem in 5G networks, while Chabira et al. (2025) highlighted that DL and ML can solve issues of 5G network through predictive analysis, adaptive mobility, and load control. However, issues of limited dataset availability, lack of model which are energy efficient and model which integrates context aware and real-time decision systems are still unsolved issues.

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Anand et al. (2023) proposed Machine Learning Multi-Classification and Offloading Scheme (MLMCOS) to mitigate co-tier interference. The approach classifies users into multiple classes and then applies a service-based priority system for load balancing. Comparative analysis considering classic proportional fair scheduling algorithm, variable radius and proportional fair scheduling algorithm, and cognitive approach considering delay, throughput and packet loss recorded MLMCOS as the best. In the same pattern, K-nearest neighbor was integrated with Nelder-Mead, GA and Sequential Least Square Programming (SLSP) respectively to predict the distance between users and base station in different network condition and environment. To improve computational speed, the K-D Tree search strategy was proposed. Comparative analysis of the methods positioned K-NN + SLSP as the best in terms of prediction speed. The study successfully provides a system that can be applied as a foundation to develop a quality of service mechanism in 5G network. Cheng et al. (2020) argued the need to tackle issues of user association and resource allocation in HetNet. To solve the problem, multi agent Q-learning was proposed to improve the association of user and resource allocation, putting into consideration factors like load ratio, and base station, while DQN was applied to optimize state and action spaces. An experimental test was carried out on the model in coupled and decoupled versions. Similarly, Li et al. (2020), used a heuristic algorithm to improve DQN, to map out 5G on-demand services. Overall the results showed increased capability in spectral efficiency and system performance.

Network slicing is another approach proposed to solve congestion and interference problems in literature. For instance, Shi et al. (2020), proposed Reinforcement Learning (RL) for network slicing; likewise, an ML-based network sub-slicing framework in sustainable 5G environment was proposed by Singh et al. (2020). In the paper, the slices were separated into virtual sub-slices, while a support vector machine was applied to solve a similar problem. More ML algorithms (Extra Tree, AdaBoost, SVM, extreme gradient boosting (xGB), Light Gradient Boosting Machine (LGBM), K-NN, and Multi-Layer Perceptron (MLP) were compared in Rajak et al. (2023) for network slicing. In general, while these works have all contributed positively to the management of 5G network challenges, Nasser et al. (2025) argued that load balancing problem is complex and cannot be solved by a single model effectively. In addition, none of the studies clearly address issues of congestion and interference in the network simultaneously.

2.2 Related works on 5G service quality optimization using DL techniques

DL-based Block Coordinated Descent Simulated Annealing (BCDSA) and DL-Based Genetic Algorithm (GA) were compared in Albanna et al. (2020) to solve the issues of congestion in 5G network. GA recorded real-time improvement in throughput, signal strength, and performance overhead, against BCDSA. This work demonstrated the capability of DL in solving network optimization problems. More advanced DL was proposed in Zhang et al. (2020) who applied U-Net to model the association matrix between a user and its serving cell. The model was trained with a network traffic dataset obtained with a heuristic algorithm. The output after testing revealed increased user service performance at the cell edge. In the next paper, quantum DL was proposed to optimize communication qualities like LB, system availability and network slicing in 6G. Convolutional neural network and recurrent neural network were combined and trained as the quantum model. The results showed high success in correctly managing congestion with the 6G network. However, the model lacks interference awareness.

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Alhazmi et al. (2020) focused on signal detection in 5G, 3G and Long Term Evolution Network (LTEN). Data obtained from the different network where merged and then applied to train LeNet. This model was then deployed for signal detection in wireless networks. This model provides a platform to integrate control solutions and solve issues of congestion and interference in wireless network. Godala et al. (2020) proposed CNN to estimate radio state channel information. In the same vein, Klus et al. (2020) recommended CNN for position estimation between user and service cell in 5G network, while Doan and Zhang (2020) recommends CNN for detection of 5G network challenges. These studies have all revealed different capabilities of CNN and present the model as a potential candidate for prediction of traffic in 5G network.

A hybrid approach was proposed in Khan et al. (2022) who combined long short-term memory (LSTM) and CNN for the prediction of network slicing from incoming packets and load balancing. CNN was applied for network slicing and resource allocation, while the LSTM was used for load balancing. The application revealed a decrease in energy usage and improved network stability. Zheng et al. (2025) defined LB as a non-convex problem. The study proposed a channel selection and power allocation algorithm based on game theory approach for successful resource allocation, while to optimize the speed, a deep neural network was applied. Finally, the short packet coding rate was used to detect rate loss in the finite block length regime. However, despite the speed of DL for resource allocation, the study lacks time series awareness of congestion and interference problem, which is critical for real-time load balancing. Kimbugwe et al. (2021) studies the application of different DL model for service quality optimization in Internet of Things networks, while Khan et al. (2022) proposed a hybrid DL model constituting CNN+LSTM for predicting unknown network requests, load balancing, and optimum resource utilization. The result reported 95.17% accuracy when trained on multiple input devices, while 96.46% slicing prediction accuracy was reported for known devices.

Research Gap:

From the review of the literature, it is clear that ML and DL have dominated recent studies on 5G quality of service optimization; however, no work has improved a sector-based approach using a clear channel assessment algorithm and channel nulling technique. Secondly, there is no work with joint interference and congestion awareness during load balancing in 5 G networks. These identified gaps will be dealt with in this paper through the modeling of an intelligent sector-based approach for congestion and interference-aware load balancing in 5G heterogeneous networks.

3. METHODOLOGY

The methodology for this study is quantitative. The research design includes modeling the 5G HetNet, formulating the joint congestion and interference problem, and collecting network traffic data in selected Nigerian locations. It also involves data preparation and training of ML and DL models. Results are then presented and a comparative analysis of the trained models is performed. The study proceeds with the development of the intelligent network traffic prediction model, the proposed sector-based approach, and the integration of the intelligent sector-based approach for congestion and interference-aware load balancing in 5G HetNet. Finally, implementation on the 5G HetNet, simulation, and results discussion are conducted. Figure 3.1 presents the proposed system flowchart.

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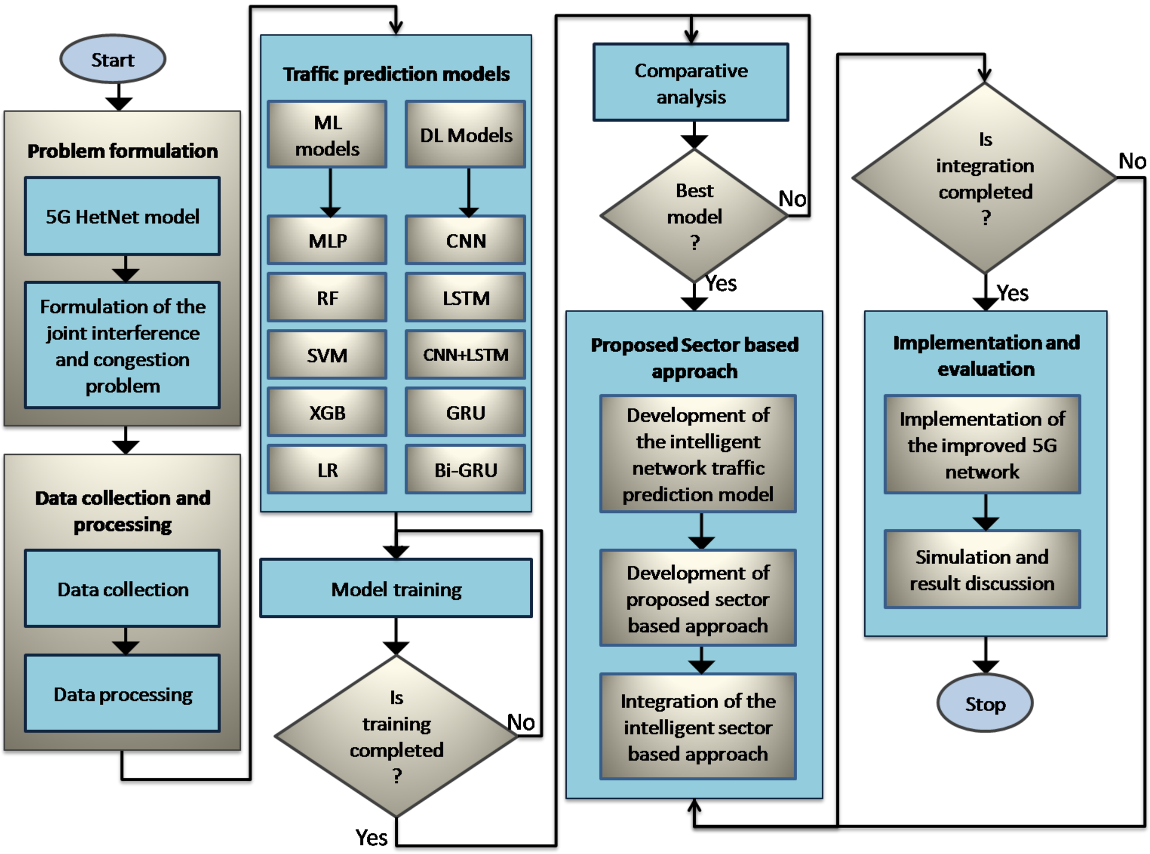

Figure 1: Proposed system flowchart

The proposed system in Figure 1 is made of five main sections. First is the problem formulation section, which begins with the modeling of the 5G network, then the mathematical formulation of the joint interference and congestion problem in the 5G HetNet. To solve the problem, 5G network traffic data is collected and processed. ML algorithms, which include multi-layered perceptron (MLP), Random Forest (RF), Support Vector Machine (SVM), Extreme Gradient Boosting (XGB), and Logistic Regression (LR) were applied.

Consequently, DL models such as CNN, LSTM, CNN+LSTM, Gated Recurrent Unit (GRU), and Bi-directional GRU (Bi-GRU) were also applied in this work. The ten models were trained and compared to identify the most suitable for prediction of network traffic. A sector-based approach was proposed and integrated with the intelligent prediction model to curate the novel intelligent sector-based approach. This was then deployed on the 5G network, implemented using simulation, and evaluated through discussions.

3.1 The 5G Heterogeneous Network Modeling

The 5G network comprises of three main cells which are the macro cell, pico cell and micro cell as shown in Figure 2. The macro is the main cell which is supported by two smaller cells. The cell coverage area in red is the region which the small cells can manage their users, while the large coverage area is the area which can e completely managed by the macro cell. The user equipments are the smart phones, laptops, offices and vehicles which are connected to the cells through the signal waves.

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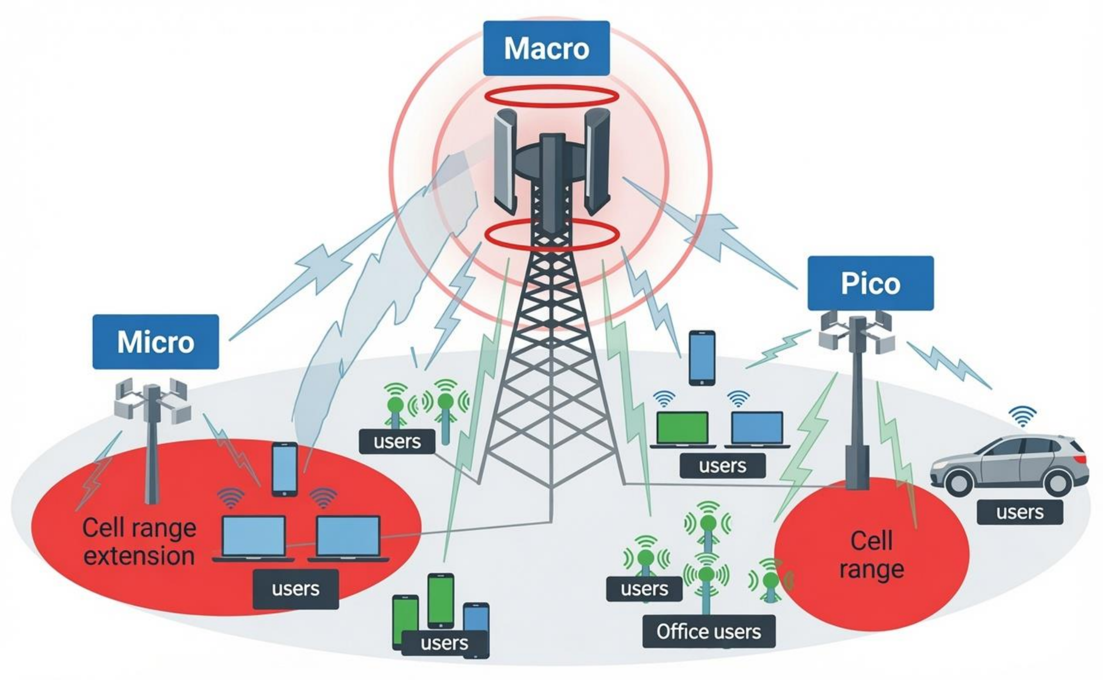

Figure 2: The architecture of the 5G HetNet

The mathematical definition of the HetNet is developed starting with the macro cell model in equation 1;

$$\text{Macro cell:} M = \{M_1, \dots \dots \dots . M_m,\ M_n \dots . , M_M) \tag{1}$$

Where $N_m = \{N_1^{ma}, \dots \dots \dots \dots M_b^{ma}, \dots \dots . . N_{N_{ma}}^{ma}\}$ is the set of the smaller cell supporting the macro cell M_{ma}. The smaller cells within the HetNet are pico in equation 2 and micro in equation 3.

$$\text{Pico cells: } P = \{P_1, \dots \dots \dots . P_f,\ P_g\ \dots \dots \dots . P_p\} \tag{2}$$

$$\text{Micro cells: Mx} = \{Mx_1, \dots \dots \dots . Mx_f,\ Mx_g\ \dots \dots \dots . Mx_p\} \tag{3}$$

Where $N_{mx} = \{N_1^{mx}, \dots \dots \dots \dots N_b^{mx}, \dots \dots . . N_{N_{mx}}^{mx}\}$ is the neighboring cell of the micro Mx_{mx}; $N_p = \{N_1^p, \dots \dots \dots \dots N_b^p, \dots \dots . . N_{N_p}^p\}$ is the neighboring cell of the pico P_p. The users operating within the cell coverage of the HetNet in equation 4 with respect to each individual cell (Nwadike et al., 2025).

$$\left.\begin{array}{l}\text{Macro Users } M_{ma} = \{U^{ma}, \dots \dots \dots \dots U_1^{ma}, \dots \dots . . U_u^{ma}, \dots \dots \dots \dots . U_{U_{ma}}^{ma}\} \\ \text{Pico cell users } P_p :\ U^p = \{U_1^p, \dots \dots \dots . . U_U^p, \dots \dots . U_{U_p}^p\} \\ \text{Micro cell users } Mx_{pi} :\ U^{pi} = \{U_1^{pi}, \dots \dots \dots . . U_U^{pi}, \dots \dots . U_{U_{pi}}^{pi}\} \end{array}\right\} \tag{4}$$

$$Subframe: S = \{1, \dots \dots \dots s, \dots \dots . S\};\ Resource\ \ blocks\ (RB) = R = \{1, \dots \dots \dots . r, \dots \dots . . , R\}$$

3.2 Mathematical formulation of the Joint Congestion and Interference Optimization problem

The 5G HetNet problem considered in this paper are congestion and interference. The problem resides at the intersection of radio resource management and network utility

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maximization, specifically interrupting the coupling between user association, power allocation and load balancing. The set of cells in the HetNet are already defined in equation 1 for the macro cell and equation 2 and 3 for the small cells respectively. We can redefine the HetNet as $B = \{B_m \cup B_s\}$ where B_m is the macro cell and B_s the small cell. $\cup$ is the user equipments. The system state is defined as $a_{ij} \in \{0,1\}$, where the binary association variables $a_{ij} = 1$ when U is connect to the cell j. the schedule variable is $x_{ikj} \in \{0,1\}$ where x_{ikj} =1if the Resource Block (RB) k is allocated to U_i by B_j. The transmission power of B_j on RB is $P_{jk} \geq 0$.

3.2.1 The interference problem modeling

The interference problem considered the signal to interference and noise ratio for U_i by B_j on the RB k and is presented for both co-tier and cross tier as equation 5.

$$\Gamma_{ijk} = \frac{P_{jk} G_{ij}}{_{m \in B/\{J\}} P_{mk} G_{im} + \sigma^2} \tag{5}$$

Where G_{ij} is the channel gain between the B and U_i, incorporating pathloss and shadowing, σ^2 is the Gaussian noise power. Shannon capacity was used to determine the data rate for U_i associated by B_j is presented as equation 6 (Ben-Yishai et al., 2021).

$$R_{ij} =_{k \in \kappa} x_{ikj} . W log_2(1 + \Gamma_{ijk}) \tag{6}$$

Where W is the bandwidth of a single RB. Figure 3 presents the interference problem.

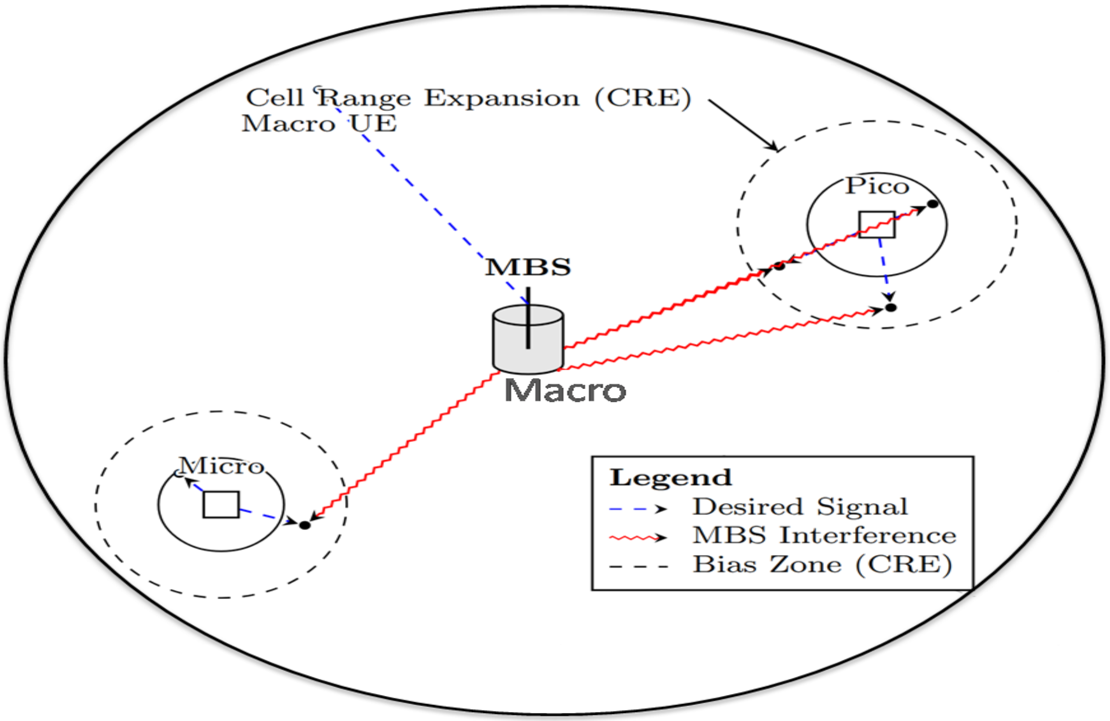

Figure 3: Macro cell interference on pico and micro cells

Figure 3, is the cell coverage area for macro cell. The cell is supported by a micro and pico cell, however the macro cell interference on the coverage region of the small cell resulting to interference problem. The desired signal is the actual signal without interference; the red signal is the interference from the macro cell, while the bias zone is the area within the small cell affected by interference.

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3.2.2 The congestion load problem modeling

The congestion load modeling is the load balancing problem which occurs when the number of RBs and processing capacity of the cell are limited and cannot manage data from users. The load of the cell is defined as B_{lj} donated by η_j as the ratio of the demanded resources to available resources.

$$\eta_j = \frac{1}{|\text{ꓘ}|} \ i \in \mu \quad k \in \kappa^{x_{ikj}} \tag{7}$$

The for the cell range extension, the associated bias is defined as equation 8;

$$a_{ij} = \mathbb{I}(j = argmax_{m \in B} \{B_m \,.\, P_m \,.\, G_{im}\}) \tag{8}$$

Where B_m is the bias factor, for $m \in B_s$ to balance the load on the macro cell. The optimization problem is therefore formulated as a non convex mix integer non-linear programming problem. The objective function is to optimize the network performance while reducing congestion and interference. The problem is presented as equation 9;

$$\emptyset\,(a, x, P) =_{i \in \mu} \cup \left(\in B \ k \in \text{ꓘ} \quad x_{ijk} W log_2 \ 1 + \frac{P_{jk} G_{ij}}{m \neq j^{P_{mk} G_{im}} + \sigma^2} \right) \tag{9}$$

3.2.3 Data collection and Processing

The data used for this work is the historical 5G MTN Nigeria network traffic data obtained from Nwadike et al. (2025). The parameters considered for the data collection are Reference Signal Received Power (RSRP), latency, throughput, packet loss, seed of the drive test vehicle, channel quality indicator, reference signal receive quality, physical resource block, active users, handover count, handover success rate, distance from serving cell, interference power, user equipment, and load factor. The data is for upstream. The cell operation period is March, 2025 and July, 2025. The reason for these periods was to capture the dry and rainy seasons. The region considered is Enugu State Metropolis. The Lat is 6°.38 to Long 7°.62. A total of eight different small cells were considered within the region, and the user activities include live video streaming, phone calls, file transfer, and internet call. The main software tool for the data collection is the licensed TEMS software, and RantCell installed in mobile phones. The total size of the dataset is 8427, with a total of 25 attributes. Furthermore, the dataset of 5G network traffic from MTN at Uwani, Enugu State was collected from Nwadike et al. (2025). This dataset was used for external model validation after training.

The data were processed in two phases to be suitable for training both ML and DL models. In the first phase, the features were separated to match the targets column. Then categorical features like the cell ID, UE categories were transformed to numeric using the one-hot encoding technique. Date and time were dropped from the dataset using recursive feature elimination techniques to reduce dimensionality, and also since our major focus in the paper are congestion and interference, which are location-based, considering factors like user density, population, and user equipment, date and time are not very relevant. The correlation matrix of the feature distribution was reported in Figure 4. Class distribution analysis was carried and it was observed that 529 records have congestion, while 7898 has no congestion. To solve this problem, Synthetic Minority Oversampling Technique (SMOTE) was applied to balance the class. The data was then split into training and testing set in the ratio of 70:30. The second phase prepared the dataset for DL training suitability. This process was built upon the steps taken for ML. After the class balance, numeric features were standardized into mean and standard deviation using StandardScaler. This is particularly important for optimal training of

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neurons. The data was then reshaped with the sliding window technique. This meets the input requirement of the 1D CNN, GRU, and LSTM. The data splitting for the DL is 80:10:10 for training, testing, and validation sets, respectively.

3.3 The Traffic Prediction Models

This paper trained two categories of model which are classical ML and DL techniques. For each category 5 different models were considered. The reason was to experiment the performance of the different model in learning the sequential and changing traffic patterns on the 5G HetNet to predict congestion problem. The ML models applied are MLP, RF, SVM, XGB, and LR, while the DL models are CNN, LSTM, CNN+LSTM, GRU and Bi-GRU.

3.3.1 ML Models

MLP: this is a type of feed forward neural network with three hidden layers (512, 256, 128), and rectified linear unit activation function. The network layer is made of neurons and bias. This allows the learning complex network patterns through back propagation algorithm and weight optimization via Adam optimizer until tolerable error is achieved. **RF:** This is an ensemble techniques made of several decision trees using bootstrapped samples and random feature selection. Their prediction is aggregated through majority voting to improve performance and reduce overfitting. **SVM:** This is a supervised learning algorithm which determined the optimal hyperplane maximizing the support vector classes in high dimensional space. This is achieved with kernel function. **XGB:** This is a scalable gradient descent boasted framework which used sequential decision trees, with each tree correcting residua error made by previous tree applying optimized gradient descent and regularization technique. **LR:** This is a linear classifier which estimates the probability of an outcome using sigmoid function. In this work, the network parameters are used to model the target class through likelihood estimation.

3.3.2 DL Models

CNN: This DL model is made of input layer with 128 sequence length, 18 multivariate channels abd batch size of 1, the convolutional layers are three and have filters (64, 128, 256), kernel sizes (5,5,3), stride=1 all through, and same padding. Max pooling layers was used with kernel size of 2 and stride of 2 after each convolution, dropout rate is 0.25, rectified linear unit activation function and two fully connected layer with 512 and 256 neurons, ReLU, and 0.3 dropout. The convolutional layer utilize for convolutional scan on the input data to identify spatial features, then the pooling layers extracts the features to the fully connected where neural network is trained. **LSTM:** This is a recurrent neural network which can learn long term dependencies in sequential data through memory cells, input, forget and output gates. It has 256 hidden size, two stack layers and dropout of 0.25.

CNN+LSTM: This is a hybrid combination of CNN and LSTM. The 3 layered 1D-CNN is used for sequential feature extraction and LSTM with 256 hidden size, 2 stacked layers, and dropout of 0.25 was used for modeling temporal dependencies in time series network behavior. **GRU:** This is similar to LSTM but with update and reset gates only. It has 256 hidden size, two stack layers and dropout of 0.25. It offers computational efficiency and maintains strong performance on sequential data. **Bi-GRU:** This is an improved version of GRU, which can process input sequence in forward and backward direction. This allows the model to learn the network behavior in past and future time series. The hidden size is 192, two bidirectional layers, and 0.3 dropouts.

3.3.3 Model Training and technical specifications

The training was carried out in Google Colab Pro platform. The RAM is 12.7GB, GPU is Tesla t4 (16GB, VRAM), CUDA version is 12.2; programming language is Python Version 3. The ML model training began with the LR which was trained with two regularization technique, INVERSE OF regularization strength C is 2.0, class weight = balanced, a liblinear solver, and max iteration of 1500. The MLP training was done with Adam optimizer, learning rate is 0.001, solver is Adam, and max iteration =1000, epoch =150. The SVM was trained using radial bias function kernel to handle high dimensional data. During the training process, the regularization parameter C=12 and the kernel coefficient γ are optimized. The RF which has 400 trees each tree represents sample of the network data. Maximum voting is applied to make prediction, max depth =25, min samples split = 4, criterion is gini, while for the XGB, a learning rate of 0.03, depth of 8, subsample ratio of 0.8, colsample by tree=0.85, number of estimators =500 and early stopping were applied to train the model. The DL models were trained on the same Google Colab environment with similar specification. All DL training were carried out with 150 epochs, batch size of 128, adam optimizer, learning rate of 0.001, weight decay of $1e-5$, and early stopping. To validate the models, the Enugu State 5G network traffic dataset from Nwadike et al. (2025) was adopted and test the model prediction performance.

3.3.4 Performance evaluation metrics

The metrics considered for performance evaluation are Mean Square Error (MSE), Coefficient of Determination (R^2), and Root Mean Square Error (RMSE). MSE measures the average squared difference between the actual and predicted congestion. The RMSE represents the square root of the average squared prediction error and provides the error magnitude in the same unit as the original data. R^2 Evaluates how well the forecasting model explains the variance in the observed data.

$$MSE = \frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2 \tag{10}$$

Where MSE is the mean square error, $\hat{y}_i$ is the predicted congestion value, y_i is actual observed congestion value, N is the total data size.

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (y_i - \hat{y}_i)^2} \tag{11}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{N} (y_i - \bar{y}_i)^2} \tag{12}$$

3.4 Sector based traffic control Model

The sector based traffic control model we proposed in Nwadike et al. (2024) was adopted. This is focused on solving the detected congestion problem, while avoiding interference. When the prediction model detect the congestion issues, the frequency division multiplexing (Vaeed et a., 2023) was applied to assign band to the each cells with the HetNet, then sectorization of the cell is applied with orthogonal frequency division multiplexing technique (Naveed et a., 2023) was applied to split new frequency band into super carrier channel for resource allocation. To ensure interference does not interference in the channels, the SNR model in equation 13 was applied to check if interference is in the channel.

$$SINR = \frac{P_{signal}}{P_{noise}} \tag{13}$$

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To manage the interference proem if in the channel, Carrier Annulling Algorithm (CAA) (Najlah and Sameer, 2020) was proposed in figure 4 while the Clear Channel Assessment (CCA) (Paul, 2020) in figure 5 was applied to prevent collision with busy channel using time control function to monitor channel engagement until they are free. He delay time is 10ms, and then set threshold for detection of interference is <15dB (Meraki, 2023). The integrated CAA and CCA based sector based traffic control for load balancing and interference management is in figure 6 while the algorithm is presented;

Proposed Sector based algorithm (Algorithm 1)

```
1.    Start
2.    Initialization of parameters
3.    Identify network parameters like carrier frequency and SNR
4.    Apply the SNR to detect to identify if channel has interference
5.    Annul interference channel selection with CAA in figure 4
6.    Sectorized cell into segments using FDM
7.    Create sub-carrier channels for each segment with OFDM
8.    Apply CCA in figure 4 to detect busy channels
9.    Assign channel for resource allocation
10.   Return to CCA
11.   End
```

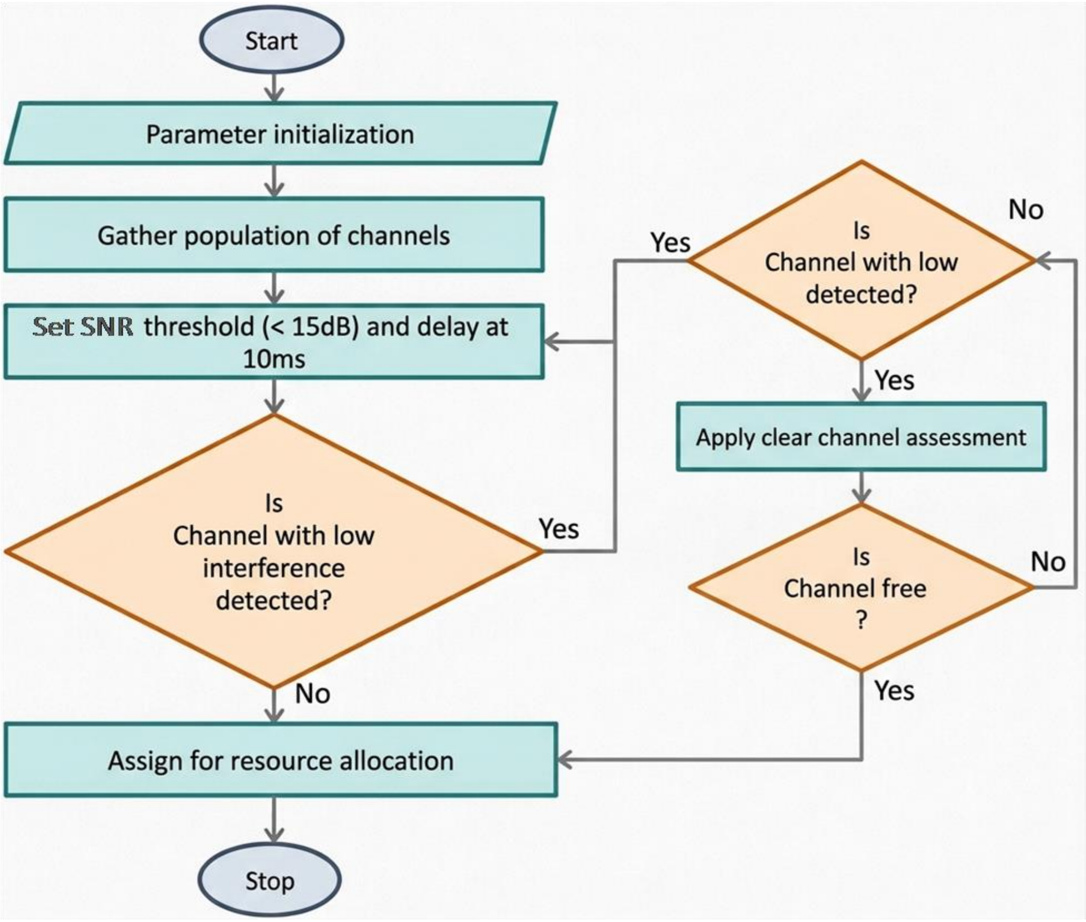

Figure 4: Flow chart of the proposed CAA for interference channel annulment

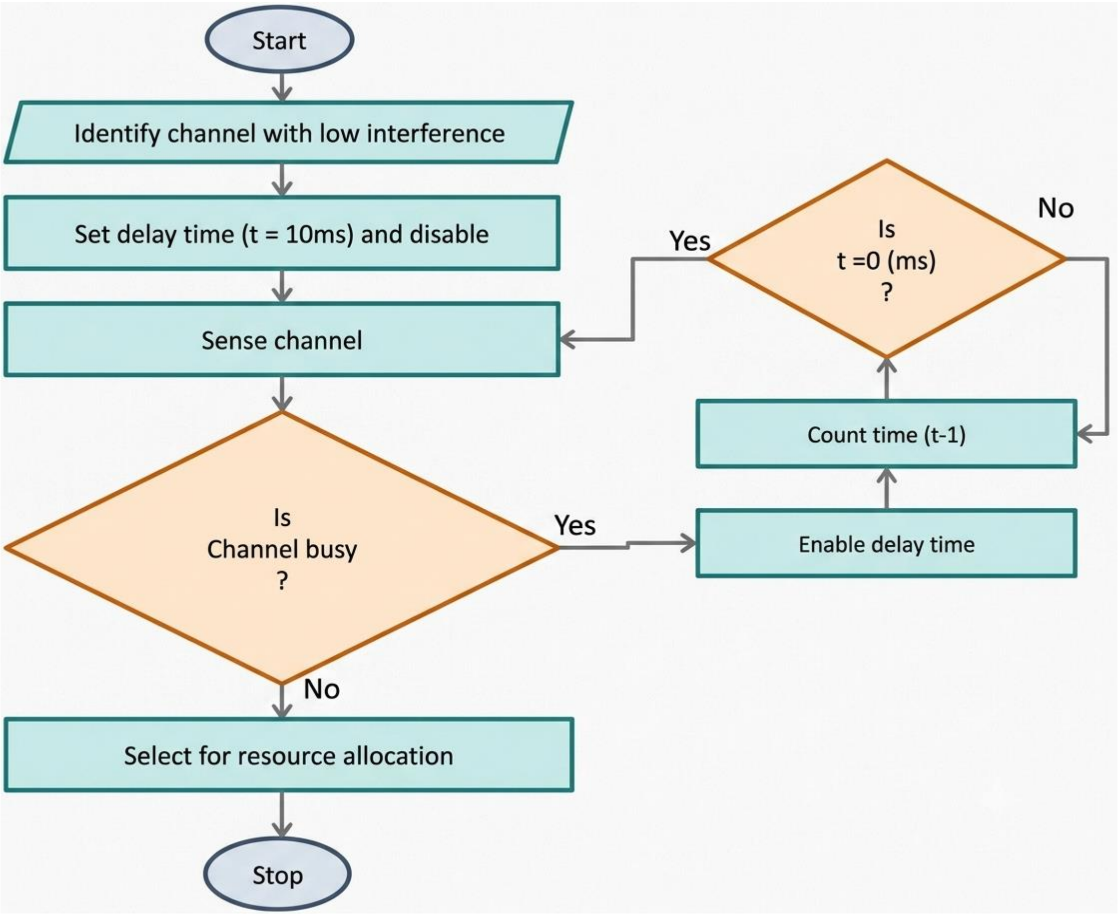

Figure 5: The CCA flow chart for busy channel management

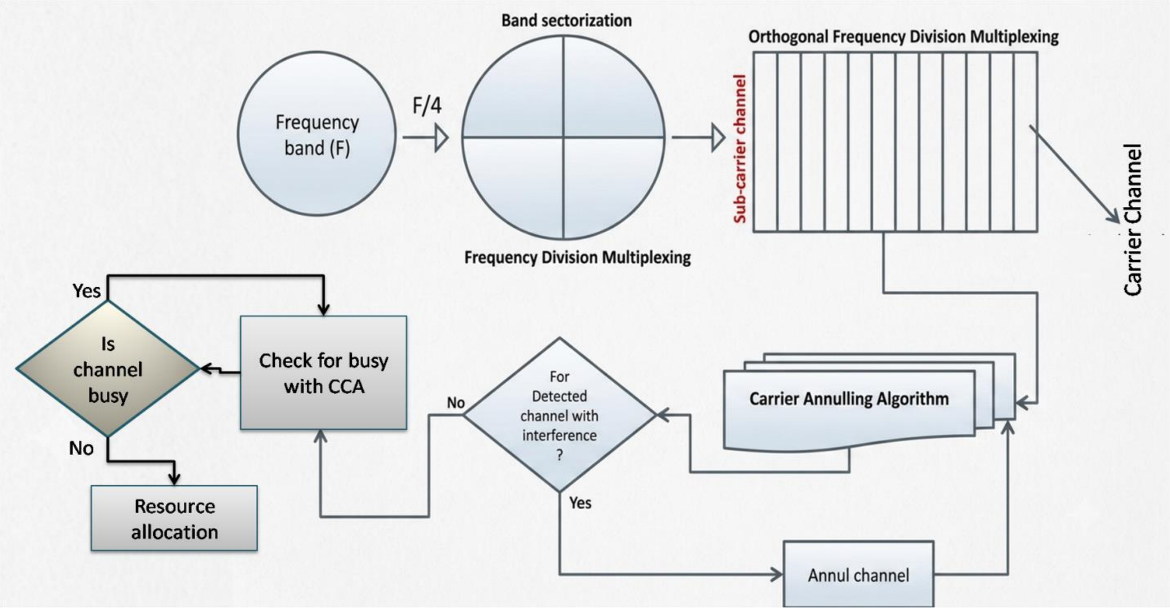

Figure 6: Architecture of the sectorized control model

Figure 6 presents the sectorized control model for load balancing and interference management in 5G network. Initially during upstream the carrier frequency of the packet is identified and then sectorized using FDM, while the sub-carrier channels are identified with

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OFDM. Equation 14 was then applied to identify level of interference on the channels and when <15dB, the channel is assigned to CCA in figure 5; else the CAA in figure 4 was applied to annul the channel. Subsequently the CCA was applied to check if channel free from interference are not busy, before assignment for resource allocation and then vertical handover (Onuigbo and Ogili, 2023) applied to distribute the resource to other small cells. The complete system flow chart of the sectorized control model with handover is presented in figure 7.

3.5 The intelligent sector based approach for load balancing and interference mitigation

This section presents the integration of the prediction model and then the proposed sectorized control model to curate the novel intelligent based sectorized control model for congestion and interference management in 5G network. First the intelligent prediction model was adopted to predict network condition. Upon prediction of congestion, the incoming packets on the network are immediately sectorized and the carrier frequency and sub-carrier channels are identified and check for interference and congested. Interference channel are annulled with CAA while congested channel are sensed and detected with CCA. Free channel from these problems are assigned resources and then handover to neighboring cells within the HetNet to balance the load. The novel deep learning based sectorized algorithm is presented;

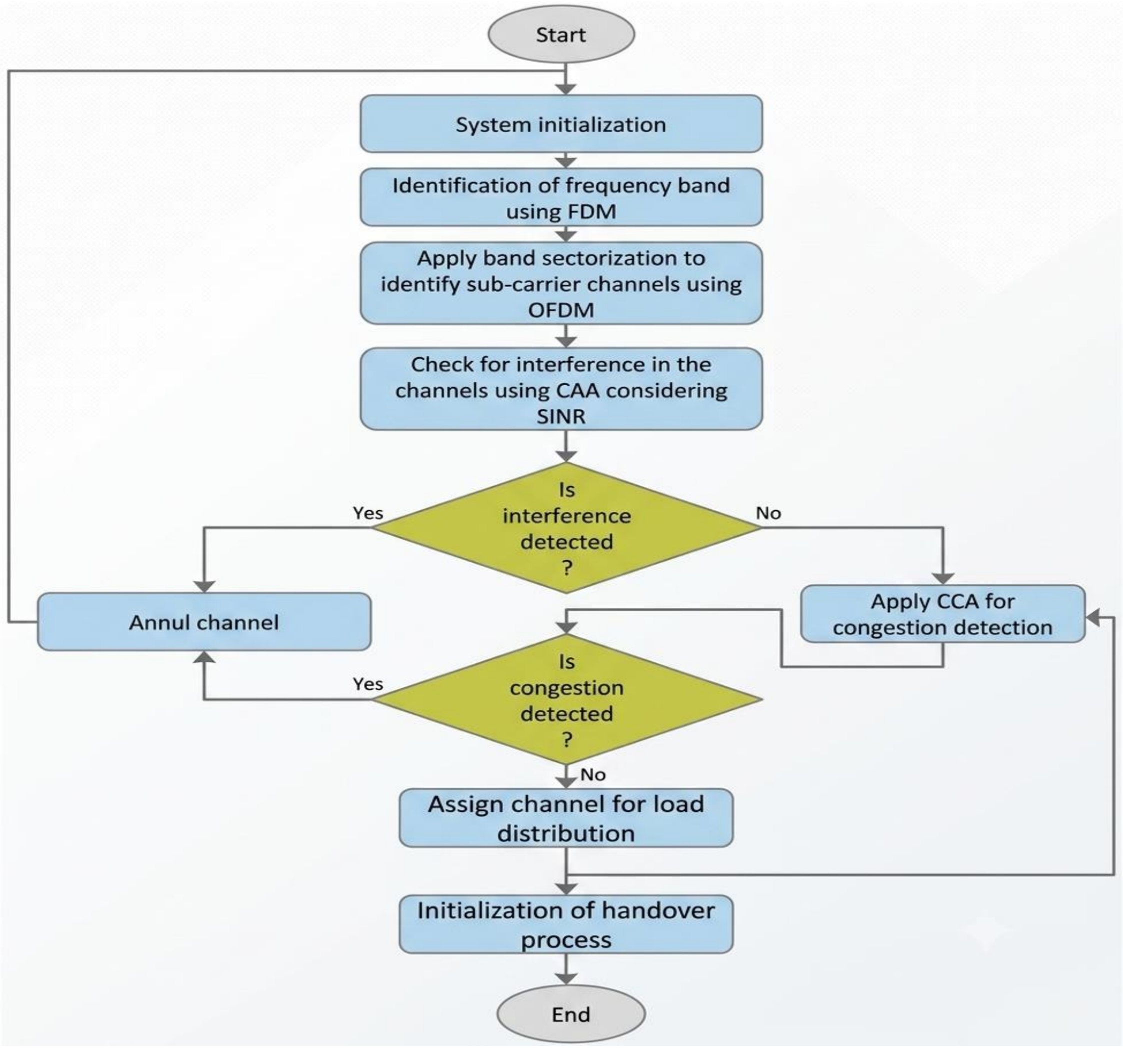

Figure 7: Sectorized control model with vertical handover

Novel Intelligent based sectorized algorithm (Algorithm 2)

```
1.  Start
2.  Initialization of parameters
3.  Collect network information from HetNet cell
4.  Feature identification by the trained prediction traffic model
5.  Prediction analysis on the model
6.  For
7.      Congestion =true
8.      Activate Algorithm 1 %% sectorized algorithm
9.  Else
10. Return to step 3
11. End
```

3.6 Simulation of the 5G HetNet with intelligent sector based control model

The simulation was carried out in a Python programming environment. The intelligent sector-based congestion and interference management model was implemented on the 5G HetNet using the simulation parameters in Table 5. The XGB classifier monitors incoming network parameters to predict congestion. The 5G network was modelled with numpy.random.randint, which mapped out the traffic from incoming packet and sectorized. The CCA and CAA were implemented with NumPy and Pandas which continuously analyze channel blocks to detect interference and avoid congestion. The simulation also compared the intelligent sector-based model against the static sector-based model. In addition, recent congestion control models like proportional fair (Seliem et al., 2025) and Deep Reinforcement Learning (RL) (Emirhan et al., 2025) were also compared through simulation.

Table 5: Simulation parameters of the 5GHetNet (Nwadike et al., 2025)

Parameters	**Values**	**The Macro Cell Station**	
Carrier frequency of cell	2.6GHz	**Parameters**	**Values**
System bandwidth	800MHz	Transmission power	46dBm (40W)
Congestion; non congestion data	161; 839	Radio access network	LTE
Shadow fading	9.22dB	Bandwidth	10MHz
Pathloss exponent	3.79	Antenna gain	15dBi
Channel model	3GPP SCM	Number of Subcarrier downlink	150
UE gain UE noise speed	560km/h	Frequency of subcarrier	180kHz
Inter site distance	500m	Antenna height	20m
Noise spectral density	-175.1dBm/Hz	Cell load ratio	0.95 to 1.05
Special sub frame ratio	2/8 (1 ABS + 1 RPS)	Distance in radius for cell range	1-20km
Packet types	Voice, streaming, file trasfer	Traffic load target (Mb/s/km^2)	850
Channel model	Typical Urban	**Pico Cell Station**	
Modulation	64QAM	**Parameters**	**Values**
Sub-frame duration	1s	Transmission power	22dBm (1W)
Subcarrier number	12	Reduced transmission power	11dBm(12mW)
Time window size	9	eNodeB Antenna gain	2dBi
Frequency window size	13	Antenna height	12.8m
Specification for VOIP	2 x 88bit	Distance in radius for cell range	47m
Number of user sector	150	Cellular layout	Non uniform

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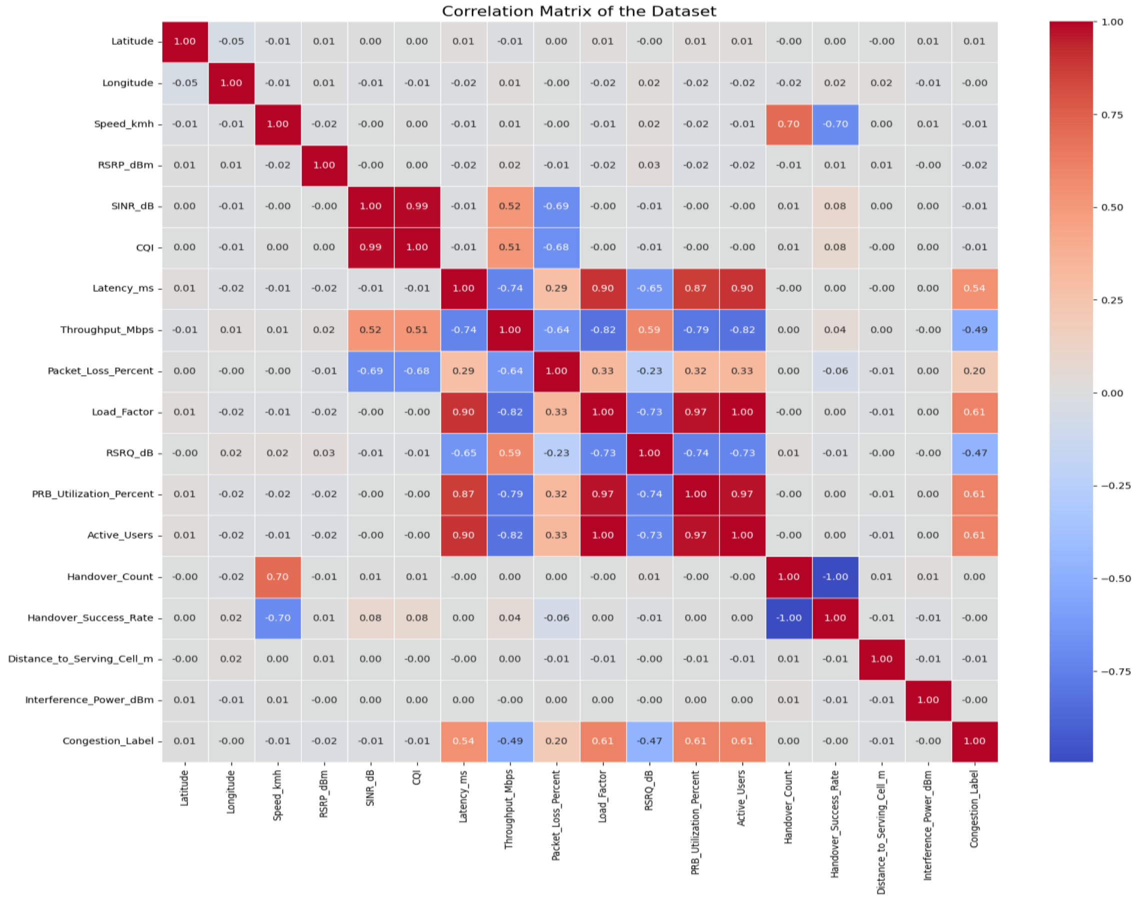
Micro Cell Station	
Parameters	**Values**
Transmission power	62dBm
Site type	Single sector
Reduced transmission power	13dBm(14mW)
eNodeB Antenna gain	7dBi
Antenna height	10m
Distance in radius for cell range	200m-1km

4. RESULTS AND DISCUSSION

This section presents the result and discussion of the paper. First the correlation matrix representation of the 5G Network data collection was provided in figure 8. The diagram showed the relationship s between each attributes in the dataset and how they collective model the target value which is congestion.



	Latitude	Longitude	Speed_kmh	RSRP_dBm	SINR_dB	CQI	Latency_ms	Throughput_Mbps	Packet_Loss_Percent	Load_Factor	RSRQ_dB	PRB_Utilization_Percent	Active_Users	Handover_Count	Handover_Success_Rate	Distance_to_Serving_Cell_m	Interference_Power_dBm	Congestion_Label
Latitude	1.00	-0.05	-0.01	0.01	0.00	0.00	0.01	-0.01	0.00	0.01	-0.00	0.01	0.01	-0.00	0.00	-0.00	0.01	0.01
Longitude	-0.05	1.00	-0.01	0.01	-0.01	-0.01	-0.02	0.01	-0.00	-0.02	0.02	-0.02	-0.02	-0.02	0.02	0.02	-0.01	-0.00
Speed_kmh	-0.01	-0.01	1.00	-0.02	-0.00	0.00	-0.01	0.01	-0.00	-0.01	0.02	-0.02	-0.01	0.70	-0.70	0.00	0.01	-0.01
RSRP_dBm	0.01	0.01	-0.02	1.00	-0.00	0.00	-0.02	0.02	-0.01	-0.02	0.03	-0.02	-0.02	-0.01	0.01	0.01	-0.00	-0.02
SINR_dB	0.00	-0.01	-0.00	-0.00	1.00	0.99	-0.01	0.52	-0.69	-0.00	-0.01	-0.00	-0.00	0.01	0.08	0.00	0.00	-0.01
CQI	0.00	-0.01	0.00	0.00	0.99	1.00	-0.01	0.51	-0.68	-0.00	-0.01	-0.00	-0.00	0.01	0.08	-0.00	0.00	-0.01
Latency_ms	0.01	-0.02	-0.01	-0.02	-0.01	-0.01	1.00	-0.74	0.29	0.90	-0.65	0.87	0.90	-0.00	0.00	-0.00	0.00	0.54
Throughput_Mbps	-0.01	0.01	0.01	0.02	0.52	0.51	-0.74	1.00	-0.64	-0.82	0.59	-0.79	-0.82	0.00	0.04	0.00	-0.00	-0.49
Packet_Loss_Percent	0.00	-0.00	-0.00	-0.01	-0.69	-0.68	0.29	-0.64	1.00	0.33	-0.23	0.32	0.33	0.00	-0.06	-0.01	0.00	0.20
Load_Factor	0.01	-0.02	-0.01	-0.02	-0.00	-0.00	0.90	-0.82	0.33	1.00	-0.73	0.97	1.00	-0.00	0.00	-0.01	0.00	0.61
RSRQ_dB	-0.00	0.02	0.02	0.03	-0.01	-0.01	-0.65	0.59	-0.23	-0.73	1.00	-0.74	-0.73	0.01	-0.01	-0.00	-0.00	-0.47
PRB_Utilization_Percent	0.01	-0.02	-0.02	-0.02	-0.00	-0.00	0.87	-0.79	0.32	0.97	-0.74	1.00	0.97	-0.00	0.00	-0.01	0.00	0.61
Active_Users	0.01	-0.02	-0.01	-0.02	-0.00	-0.00	0.90	-0.82	0.33	1.00	-0.73	0.97	1.00	-0.00	0.00	-0.01	0.00	0.61
Handover_Count	-0.00	-0.02	0.70	-0.01	0.01	0.01	-0.00	0.00	0.00	-0.00	0.01	-0.00	-0.00	1.00	-1.00	0.01	0.01	0.00
Handover_Success_Rate	0.00	0.02	-0.70	0.01	0.08	0.08	0.00	0.04	-0.06	0.00	-0.01	0.00	0.00	-1.00	1.00	-0.01	-0.01	-0.00
Distance_to_Serving_Cell_m	-0.00	0.02	0.00	0.01	0.00	-0.00	-0.00	0.00	-0.01	-0.01	-0.00	-0.01	-0.01	0.01	-0.01	1.00	-0.01	-0.01
Interference_Power_dBm	0.01	-0.01	0.01	-0.00	0.00	0.00	0.00	-0.00	0.00	0.00	-0.00	0.00	0.00	0.01	-0.01	-0.01	1.00	-0.00
Congestion_Label	0.01	-0.00	-0.01	-0.02	-0.01	-0.01	0.54	-0.49	0.20	0.61	-0.47	0.61	0.61	0.00	-0.00	-0.01	-0.00	1.00

Figure 8: Correlation matrix of the 5G network data

The figure 8 showed clearly the attributes are perfectly distributes in the dataset because of the diagonal matrix value of 1.0. For instance the SINR has strong relationship with channel quality indicator, and throughput. Similarly it was observed that attributes like latency, throughput, packet loss, load factor, PRQ, active users all have strong relationship between themselves and also impact strongly on the target value which is congestion. In figure 8 and 9, the result of the class balance was posited.

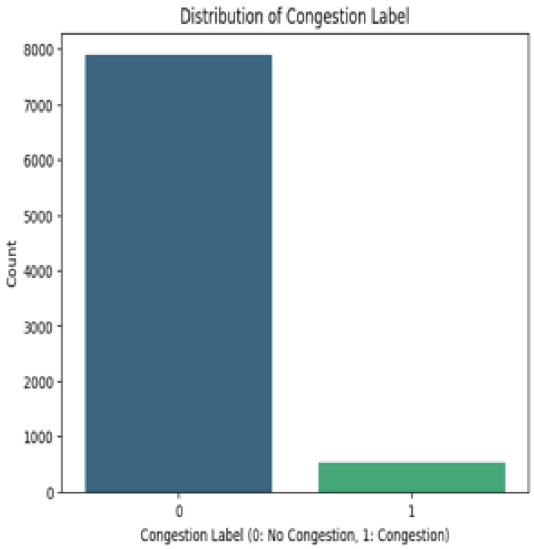


Figure 8: Imbalance class without SMOTE

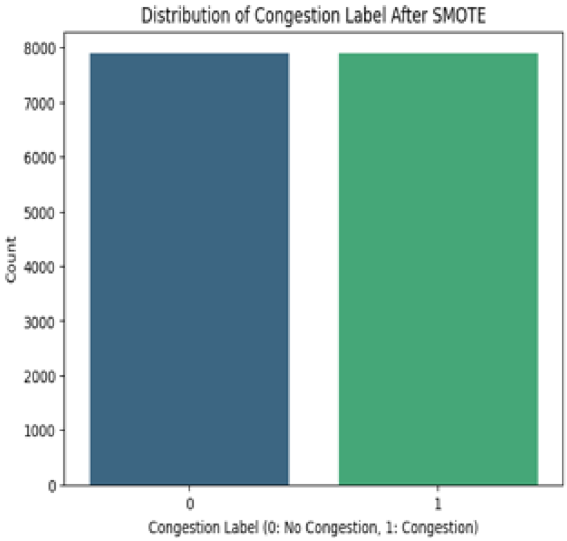


Figure 9: Balanced class with SMOTE

Figure 8 showed that the class is imbalanced with non congestion records of 7898 while congestion records are 529. The application of SMOTE to balance the class restored the records to 7898 for both classes as shown in figure 9 before the data were splitted and applied for training. Table 1 presents the comparative result of the ML model trained.

Table 1: Result of the ML model training

Model	R^2	MSE	RMSE
Multi-layer Perceptron	0.9713	0.0072	0.0847
Random Forest	0.9924	0.0019	0.0436
Support Vector Machine	0.8717	0.0321	0.1791
Extreme Gradient Boosting	0.9966	0.0008	0.0291
Logistic Regression	0.9890	0.0027	0.0524

Table 1 showed the training results of the five ML models considering several regression metrics. From the outcome, generally, it was observed that the five models recorded a very good success rate considering the errors reported at a glance. Coming down to the individual analysis, it was noticed that the MLP recorded an MSE of 0.0072, RF reported 0.0019, SVM recorded 0.0321, XGB reported 0.0008, and LR 0.0027 respectively. These results implied that XGB reported the least MSE among the five models, which is very good, indicating its ability to correctly predict congestion with the least error from the actual HetNet network state. RMSE was measured and the MLP reported 0.0847, RF recorded 0.0436, SVM scored 0.1791, XGB recorded 0.0291 and LR recorded 0.0524, respectively. The results reported revealed that the XGB RMSE recorded the lowest RMSE. This result aligned with the earlier reported value of MSE which also revealed that XGB score the least error. For the R^2 analysis the MLP recorded 0.9713, RF reported 0.9924, SVM scored 0.8717, XGB reported 0.9966, and LR reported 0.9890. These results implied that all the models reported very high prediction success rate, which is good; however, the XGB standout as the best with 0.9966 prediction success. This result means that XGB was able to correctly predict network congestion from the real-time HetNet information with a 99.66% success rate. Table 2 presents the training results of the DL models.

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Table 2: Result of the DL model training

Model	R^2	MSE	RMSE
CNN	0.9494	0.0127	0.1125
LSTM	0.9544	0.0114	0.1067
CNN+LSTM	0.9485	0.0129	0.1135
GRU	0.9510	0.0122	0.1106
Bi-GRU	0.9502	0.0124	0.1116

Table 2 presents the results of the DL model training. From the outcome, it was observed that CNN for instance, reported an MSE of 0.0127; LSTM reported 0.0114; CNN+LSTM recorded 0.0129; GRU reported 0.0122, and Bi-GRU scored 0.0124. These results showed that CNN, GRU, and Bi-GRU reported very close MSE scores; however, the lowest MSE is LSTM, which reported 0.0114. This error is tolerable as it showed the potential for a very high success rate of congestion prediction in the 5G network. The RMSE also reported CNN with 0.1125 errors, LSTM recorded 0.1067, CNN+LSTM scored 0.1135, GRU reported 0.1106, and then the Bi-GRU which scored 0.1116. These results showed that the LSTM recorded the least RMSE of 0.1067 which is good, and implied the model was able to correctly predict congestion on the network with limited error chances. R^2 readings for CNN recorded 0.9494, LSTM scored 0.9544, CNN+LSTM reported 0.9485, GRU recorded 0.9510, and Bi-GRU recorded 0.9502. In general, it was revealed that the LSTM was consistently the best across all the metrics, which is very good, and also it was noticed that the LSTM model was able to correctly predict network condition at a 95.44% success rate. Table 3 presents the comparative of the ML and DL models considering similar metrics.

Table 3: Comparative analysis of the DL and ML congestion prediction models

Model	R^2	MSE	RMSE
Multi-layer Perceptron	0.9713	0.0072	0.0847
Random Forest	0.9924	0.0019	0.0436
Support Vector Machine	0.8717	0.0321	0.1791
Extreme Gradient Boosting	0.9966	0.0008	0.0291
Logistic Regression	0.9890	0.0027	0.0524
CNN	0.9494	0.0127	0.1125
LSTM	0.9544	0.0114	0.1067
CNN+LSTM	0.9485	0.0129	0.1135
GRU	0.9510	0.0122	0.1106
Bi-GRU	0.9502	0.0124	0.1116

Table 3 compared the performance of the ten models considering coefficient of determination, MSE, and RMSE. From the result, it was observed that four of the ML models (MLP. RF, XGB, and LR) performed better than the DL model considering R^2. Similarly, for the MSE and RMSE results, all the ML models considered in this work, apart from SVM recorded lower error compared to the DL models. The results therefore implied that for the detection of congestion, ML models, specifically XGB, provided a better detection success rate compared to DL models like CNN, LSTM, LSTM+CNN, Bi-GRU and GRU, respectively. The likely reason the ML models were better in this case, despite the ability of DL models to learn complex and unstructured data might be due to the data size which might not be sufficient to provide enough information to improve the DL performance. The result of the model validation with the external MTN dataset adopted from Nwadike et al. (2025) was reported in table 4.

Table 4: External validation result of the models

Model	R^2	MSE	RMSE
Multi-layer Perceptron	0.7584	0.0142	0.1193
Random Forest	0.9195	0.0047	0.0689
Support Vector Machine	0.0067	0.0593	0.2435
Extreme Gradient Boosting	0.9799	0.0012	0.03444
Logistic Regression	0.9396	0.0036	0.0597
CNN	0.7785	0.0130	0.1142
LSTM	0.7584	0.0142	0.1193
CNN+LSTM	0.6779	0.0190	0.1378
GRU	0.7584	0.0142	0.1193
Bi-GRU	0.7785	0.0130	0.1142

Table 4 showed the performance of the ten models when tested with the external network traffic dataset. From the results it was observed that SVM recorded very poor coefficient of determination result of 0.0067. Mix of DL and ML model such as MLP, CNN, LSTM, GRU, Bi-GRU all reported R^2 of range of 0.700 to 0.7785. CNN+LSTM reported 0.6779, while superior results were observed in models like RF, XGB, and LR. Overall the XGB reported the best model performance with 0.9799 records. In the same vein, XGB recorded the least error for MSE and RMSE respectively. Therefore, the intelligent sector based congestion and interference control model was developed with the integration of XGB traffic prediction model.

4.2 Result of Simulation

The simulation result of the intelligent sector based control model on the 5G network was evaluated considering metrics such as SINR, latency, throughput and RSRQ against different user loads. The simulation as carried out and compared against the baseline static sector based congestion control. The result was reported in figure 10.

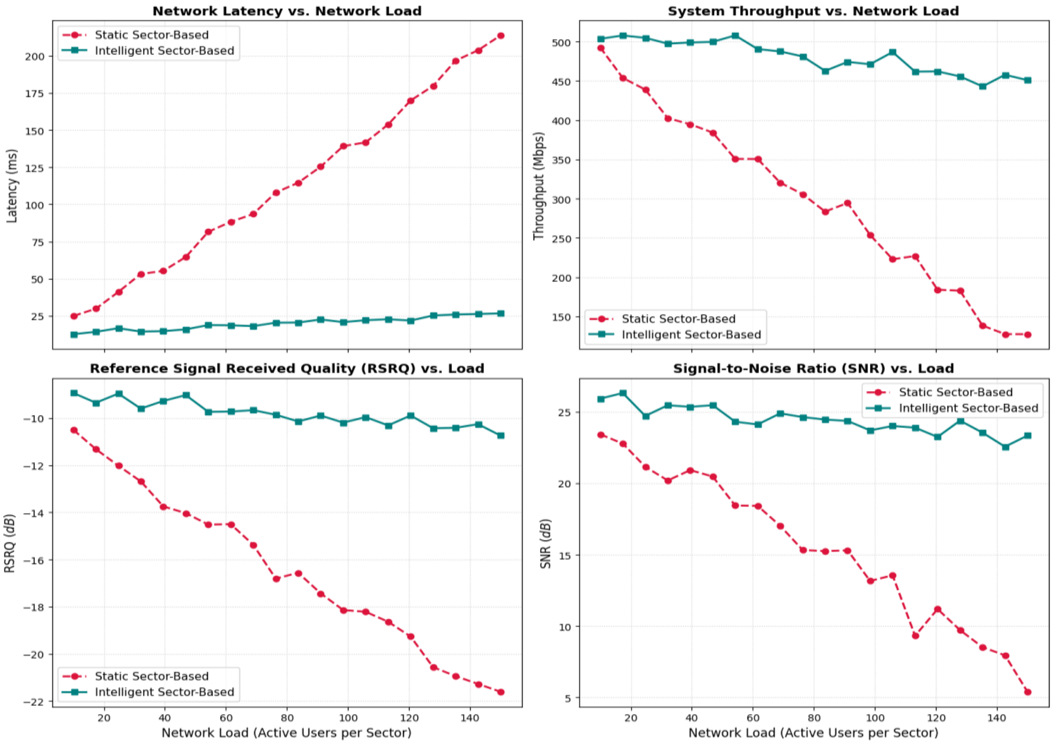

Figure 10: Simulation result of the 5G HetNet

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From the result in Figure 10, it was observed that initially, when the network load was low, the service quality was good according to the Nigerian Communication Commission (NCC) standard for 5G network best practices. For the latency, it was observed that the static sector-based approach recorded an increase in latency of up to 200ms as the network load increased beyond 140 users per sector.

The reason was because the lack of a proactive congestion detection model to trigger the sector based results to delays in load balancing and this result to the increase latency. In addition, while the static sector based can control congestion, the rapid increase of the network load within a short period of time resulted in cumulating latency, which was observed in the result. Contrary is, the intelligent sector based which utilized the XGB to predict congestion in time series after analysis of real-time network behavior from the cells. Upon prediction of congestion, the sector based used CCA and CAA to balance the load while mitigating interference.

The result showed that despite an increase in user load, the latency was relatively constant and fell below 25ms, which is very good and acceptable according to NCC standard for 5G network. The throughput in mbps also degraded with an average of 327mbps, as the user load increased for the static sector-based, while due to the predictive nature of the intelligent sector, it was able to sustain high throughput beyond 430mbps despite the active user sector reaching 150.

The percentage throughput improvement with ISB is 31.5%. The RSRQ at different load was also measured considering the Static Sector Based (SSB) and Intelligent Sector Based (ISB). The result showed that with the ISB, the quality of signal was more consistent and good with an average of -9.78 dB, compared to the SSB with 16.4dB. SINR for the two control model showed that with ISB, the signal quality was very good despite an increase in load and averagely reported 23.7dB compared to the SSB, whose signal degrades due to the impact of noise as the load factor of the cell increases.

The average SNR for SSB is 15.2dB, which is 55.9% reduction in quality compared to ISB. This SSB result demonstrated the impact of interference on the signal quality and affects user experience because there was no CAA to monitor and annul channels with interference like the case of ISB. In general, it was observed that the introduction of the XGB prediction model for early detection of traffic played a great role in fast congestion incidence response by the ISB as it ensures load on the cell is identified and control, while also addressing interference within impact on user experience.

In the next results, the simulation was carried out categorizing different user activities as shown in Figure 11. The activities considered are phone calls, live video streaming, and file transfer. At the top of the graph is phone call analysis. It was observed that the ISB maintained an average low latency of 9.93ms, despite increase network load with different sectors of users making phone calls. The SSB, on the other hand, revealed an increase in the latency value as the load on the network increases, and recorded an average latency of 21.8ms for call. Similarly, the SSB reported a highly dynamic throughput behavior compared with the ISB, which is more stable. The reason was that the networks are monitored in real time by the XGB, which collects necessary information that models the network behavior and then predicts its condition. Once congestion is detected, load balancing is activated with the proposed sector based which utilizes the CCA and CAA to manage both congestion and interference before distribution to a new cell through vertical handover.

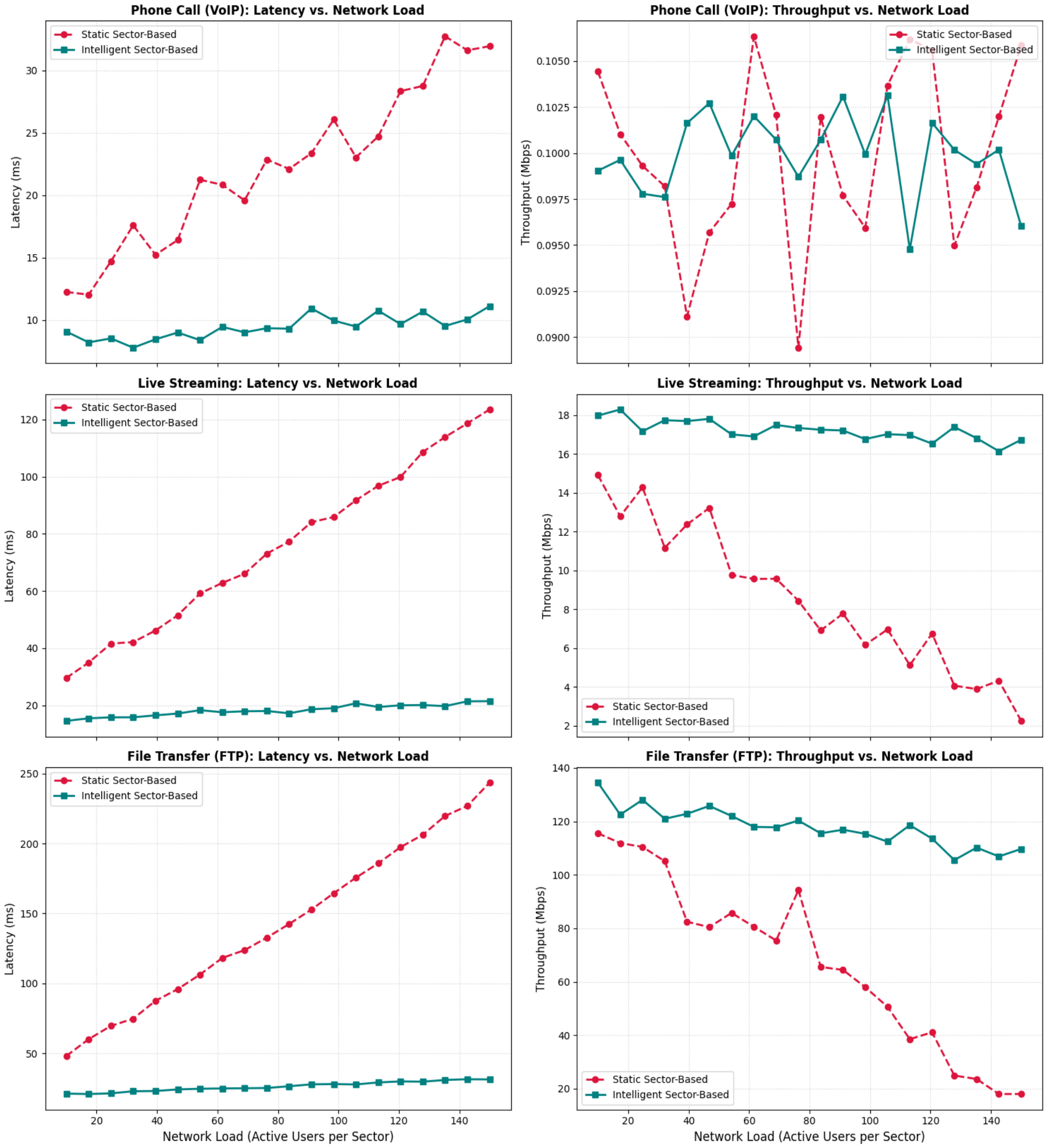

Figure 11: Network behavior consider different user activities

From Figure 11, it was also observed that during live streaming, latency recorded for SSB as the network gets loaded with more sectors of users increased with an average of 80ms. The impact is that there are potential for delay during communication, breaks in transmission, and obstruction of seamless communication flow.

The ISB, on the other hand, was able to address these issues through the prediction model which detects the congestion issues and initiates proactive load balancing. The average latency reported 17.7ms which is very good for quality live steaming.

The network throughput with ISB also reported an average of 17mbps as against the SSB which fluctuates and reported an average of 8.3mbps throughput. The results showed that user, particularly does into content creation, can be effectively managed with the ISB integrated cell

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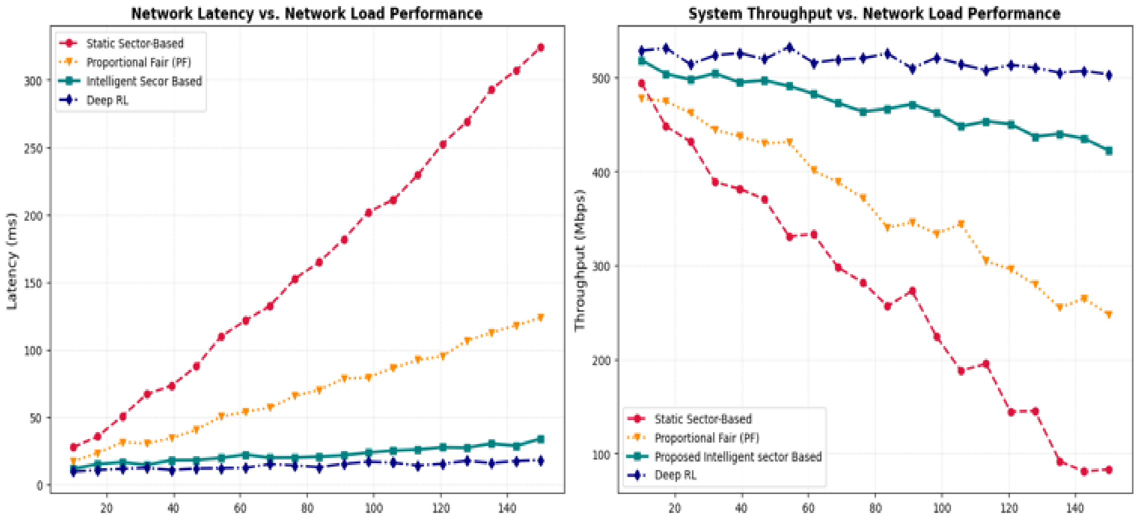
which guarantees a seamless live streaming experience without interference, delay, or break in transmission. File transfer was also considered in the last part of the graph. For the SSB, it was noticed that as the number of user which upload files increases, the latency increases steadily. This problem justified why CCA was necessary in the new ISB because it ensured that files are not transmitted on a busy channel, which can result to increase latency, as observed with SSB. The result showed an average latency of 155ms, compared to the ISB, which reported an average latency of 24 ms consistently. Similarly, the average throughput with ISB is 117mbps as against 59mbps in the SSB. The result implied that despite the increase in user number uploading files with ISB, the proactive congestion detection and the integrated CCA and CAA were able to allow fast load balancing through handover.

Figure 12 compared the SSB and ISB against some of the most recent congestion control algorithms like Deep RL (Emirhan et al., 2025), and the Proportional Fair (PF) technique (Seliem et al., 2025). The analysis was done considering users' transmission of very large files, of average 300mb. In the result of latency, it was observed that initially all the techniques recorded very low latency, less than 30ms; however, it was noticed that as the network load kept increasing, the quality of latency began to change. For instance, the SSB increases rapidly with an average of 177ms, The PF increased gradually with an average of 73ms, while the Deep RL and ISB were consistent despite the increase in network load, with an average of 21ms for the ISB and then 16ms for Deep RL. The throughput also followed the same trajectory, as the ISB reported an average of 300mbps throughput with fluctuating behavior; the PF reported 417mbps throughput average, with the overall performance decreasing as the network load increases. For the ISB, it was noted that a steadier throughput average of 462mbps was reported, while the Deep RL recorded 417mbps throughput on average. The comparative RSRQ was also evaluated for the four models. The result showed that SSB reported a sharp decrease in the RSRQ with an average of -16.3 dB; the PF recorded an average of -12.6 dB; ISB reported an average of -7 dB, while the Deep RL recorded -6.1 dB. This result showed that the Deep RL and the ISB are the two best models, which recorded the best signal quality. The Deep RL has also shown consistency in all the metrics as the best so far in controlling congestion, while our model (ISB) has also shown close consistency and competition among the best, and supersedes SSB and IPF. Finally, the SNR was applied to evaluate model performance.



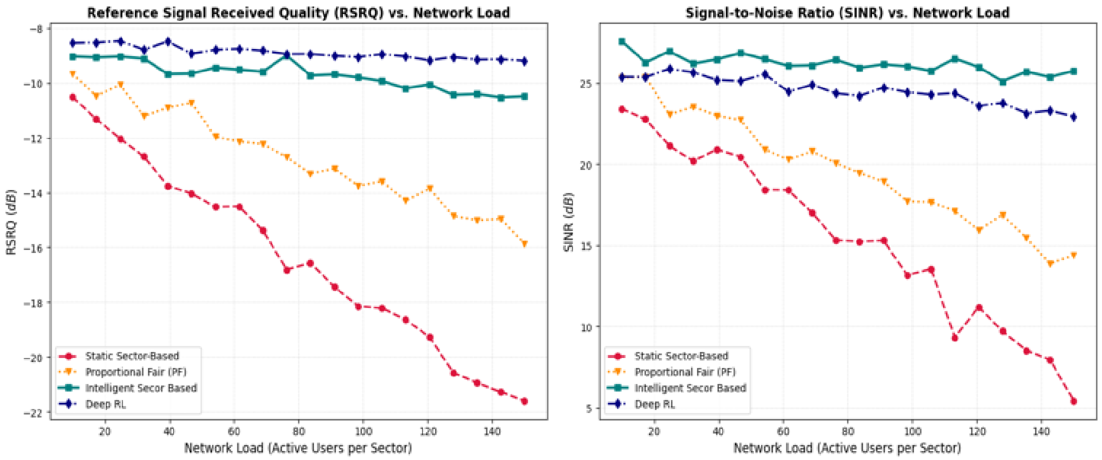


Figure 12: comparative network performance considering existing recent models

From the SNR results in Figure 12, it was observed that the SSB and PF recorded a decrease in signal quality as the network load increased. The result also showed that averagely the SSB reported 15.2dB, and the PF reported 21dB. The ISB and Deep RL reported stable SIN behavior, with an average of 23.7dB for Deep RL and then 25.1dB for ISB. Overall, it was observed that while the Deep RL dominates performance considering metrics like latency, throughput, and RSRQ, it all slightly short for SNR, as the SSB recorded the best performance, with 5.905% improvement against Deep RL, which is the second best in the existing model. These results therefore revealed that the SSB model not only competes among the best for congestion control, but, to the best of our knowledge, is the only load balancing model that also controls the interference problem.

5. CONCLUSION, LIMITATION AND SUGESTION FOR FUTURE SCOPE

This paper has successfully demonstrated that the issues of congestion and interference in 5G HetNet can be addressed through intelligent load balancing. This was achieved by developing an intelligent congestion prediction model after experimenting with five ML and DL models and identifying XGB as the best. Independent model assessment was carried out using external data obtained from the Enugu 5G cell through drive test. The prediction model was then integrated to a proposed sector-based model developed with CCA and CAA and deployed on 5G network through experimental simulation considering ISB and SSB. The results demonstrated the effectiveness of the ISB in managing congestion with 31.5% improvement against the SSB, and also interference management with 55.9% noise reduction when compared to the SSB. Comparison considering different packet types on the two models was carried out and the ISB showed consistent dominance in the service quality. Existing models like PF, Deep RL were also compared with ISB and ISS. The results showed while the Deep RL recorded the best, ISB closely competes among the best, but is the most reliable to manage interference and congestion during load balancing. The model is therefore recommended to MTN Nigeria and other telecom companies for adoption and to address congestion and interference in 5G HetNet. The limitation is the unavailability of large historical data, which limits the model's ability to network behavior considering environmental and weather conditions. Also, the used dataset was only localized to Enugu Sub-Urban environment and may not correctly characterize network conditions in areas like smart city. The cost of physical development of the new system into gNodeB was not considered in this paper. Finally, a recommendation for future score is the need to address the aforementioned limitation. In addition, while ML showed superiority over DL for traffic prediction success, future works can explore the performance of transfer learning models.

6. DATA AVAILABILITY

The data used for this study is available with the corresponding author and will be provided upon reasonable request.

7. DECLEARATION OF GENERATIVE ARTIFICILA INTELLGENCE USAGE

No generative AI tool was used to write this paper. However, grammarly was used for grammatical error check.

8. DATA PRIVACY

All data were anonymized and aggregated prior to analysis, ensuring that no Personally Identifiable Information (PII) was processed. The research adheres to the Nigeria Data Protection Regulation (NDPR) and institutional ethical guidelines.

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