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Dynamic Frequency Reuse for Enhance 5G Spectrum Management

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Abstract **- In the relentless pursuit of optimizing 5G spectrum management, this study introduces a dynamic frequency reuse scheme leveraging a symbiotic integration of Logistic Regression models and Queuing Theory. The focal point of this scheme is the seamless transition from a conservative reuse-3 pattern to a more dynamic reuse-7 configuration when the number of users surpasses 50. Through rigorous analysis and consistent observations, our findings showcase a significant enhancement in user accommodation, spectral efficiency, and overall network performance. The scheme's architecture relies on a Logistic Regression model to predict optimal transition times, while Queuing Theory principles are invoked to manage users efficiently during and after the switch. The proposed system accommodates users ranging from 51 to 65 within the reuse-7 framework, subsequently directing users exceeding this threshold to a queuing system. This innovative approach ensures that spectral resources are utilized optimally, minimizing interference, and maintaining a high quality of service. Consistent observations across various scenarios demonstrate that the dynamic transition to reuse-7 consistently results in accommodating more users within the existing spectrum. Spectral efficiency is notably improved, and the queuing system proves to be an effective mechanism for resource allocation beyond the immediate capacity of reuse-7. This abstract encapsulates the core contributions of our research, shedding light on a dynamic frequency reuse scheme that not only adapts to changing network dynamics but also systematically enhances 5G spectrum management by accommodating more users and optimizing resource utilization. The symbiosis of Logistic Regression models and Queuing Theory principles emerges as a promising paradigm for adaptive and efficient 5G network management.**

Keywords: Frequency Reuse Factor, 5G, Logistic Regression, Poisson Theory, Odd Ratio, Dynamic Switch etc.

1. Introduction

In the dynamic landscape of 5G wireless communication networks, where unprecedented data demands and diverse connectivity requirements reign supreme, the optimization of spectrum resources becomes paramount. A pivotal solution in this domain is the implementation of a Dynamic Frequency Reuse (DFR) scheme, a sophisticated strategy designed to intelligently allocate frequencies across cells (Taufique et al., 2017). This cutting-edge paradigm not only meets the evolving needs of 5G networks but does so with a novel twist integrating both Logistic Regression models and Queuing Theory for a seamless transition from the conventional reuse-3 pattern to the more robust reuse-7 configuration (Samal, 2014).

The emergence of 5G technology heralds a new era of connectivity, where ultra-low latency, high data rates, and massive device connectivity converge (Bhatia et al., 2023). To meet these ambitious benchmarks, 5G networks necessitate adaptive and intelligent spectrum management approaches. The utilization of Dynamic Frequency Reuse is instrumental in this regard, offering a responsive solution to the dynamic and diverse nature of 5G network traffic (Kurt etal., 2021).

The integration of Logistic Regression models brings machine learning prowess into the spectrum management equation. By analyzing historical data, network performance metrics, and real-time conditions, the Logistic Regression model becomes an intelligent decision-maker, predicting optimal times and conditions for transitioning from reuse-3 to the more aggressive reuse-7 pattern (Walia, 2023). This data-driven approach not only optimizes spectral efficiency but also enhances the network's adaptability to the specific demands of 5G applications.

Simultaneously, the incorporation of Queuing Theory addresses the intricacies of traffic dynamics within 5G networks. By modeling waiting lines and service processes, Queuing Theory provides insights into network congestion, latency, and traffic loads (Kochetkova et al., 2023). This information is crucial for making informed decisions on when and how to implement the

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transition between reuse patterns, ensuring a seamless and efficient adaptation to the dynamic demands of 5G connectivity. In the following sections, we will delve deeper into the mechanics of Logistic Regression and Queuing Theory integration, exploring how these methodologies synergize to enhance 5G spectrum management through the dynamic frequency reuse scheme. This intersection of machine learning and queuing principles represents a forward-thinking approach to address the unique challenges posed by 5G networks, (Mamane et al., 2021), marking a significant stride towards intelligent and adaptive spectrum resource allocation in the era of next-generation connectivity.

2. Literature Review

The need for radio spectrum expanded rapidly as a result of the growing demand for smartphones and other sophisticated devices, which encouraged the development of cellular communication applications including online gaming, group chat, video conference, and on-demand video streaming (Xiao et al., 2013). The escalating demands of 5G networks necessitate innovative approaches to spectrum management, and one such approach gaining traction is the integration of a Dynamic Frequency Reuse (DFR) scheme with advanced predictive modeling techniques. This literature review explores the current state of research and advancements in the field of 5G spectrum management, with a particular focus on dynamic frequency reuse incorporating Logistic Regression models and Queuing Theory for the transition from reuse-3 to reuse-7(Solaija et al., 2021). The infusion of machine learning techniques, specifically Logistic Regression models, into spectrum management represents a paradigm shift in the quest for intelligent and adaptive networks (Sun and Scanlon., 2019). Recent studies have explored the feasibility of utilizing historical data, network parameters, and performance metrics to train Logistic Regression models (Thota et al., 2020). These models, when integrated into DFR schemes, contribute to informed decision-making processes regarding the optimal transition from reuse-3 to reuse-7 (Solaija et al., 2021).

i) Logistic Regression

Logistic Regression is particularly suitable for binary classification problems, which aligns with the need to make decisions between dynamic frequency reuse strategies (Reuse 3 vs. Reuse 7)(Solaija et al., 2021). The probability of an event occurring, making it useful for predicting the likelihood of success or failure in the context of dynamic frequency reuse decisions. The coefficients in the logistic regression model provide insights into the importance of different factors influencing the decision to switch from Reuse 3 to Reuse 7. Logistic regression is a statistical method used for binary classification problems, where the outcome variable is categorical and has two classes (King, 2008). When the dependent variable is dichotomous (binary), it is appropriate to use regression analysis. Logistic regression, like all other regression studies, is a predictive analysis (Hellevik, O. (2009). It is used to define and explain the relationship between a single dependent binary variable and one or more nominal, ordinal, interval, or ratio-level independent variables. It is frequently used in a variety of disciplines, including epidemiology, economics, and machine learning. The model employs the logistic function (sigmoid function) to represent the likelihood that the dependent variable belongs to a specific category (Hosmer Jr et al, 2013).Here's a simple representation of logistic regression:

$$\rho(Y=1)=\frac{1}{1+e^{-(\beta_0+\beta_1 X_1+\beta_2 X_2+\cdots+\beta_n X_n}} \qquad (3.4)$$

$\rho(Y=1)$ the probability of the dependent variable being 1
e = the base of the natural logarithm
$\beta_{0,}\beta_1, \beta_{2,.....}\beta_n$ =are the coefficients
$X_1, X_{2,.....}X_n$ = are the independent variables

The sigmoid function is referred to as an activation function for logistic regression and is defined as:

$$f(x)=\frac{1}{1+e^{-x}} \qquad (3.5)$$

e = base of natural logarithms

value = numerical value one wishes to transform

The following equation represents logistic regression:

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$$y = \frac{e^{(b_0+b_1X)}}{1 + e^{(b_0+b_1X)}} \quad (3.6)$$

Logistic Regression – Sigmoid Function

Here,

x = input value
y = predicted output
b_0 = bias or intercept term
b_1 = coefficient for input (x)

This equation is similar to linear regression, where the input values are combined linearly to predict an output value using weights or coefficient values. However, unlike linear regression, the output value modelled here is a binary value (0 or 1) rather than a numeric value.

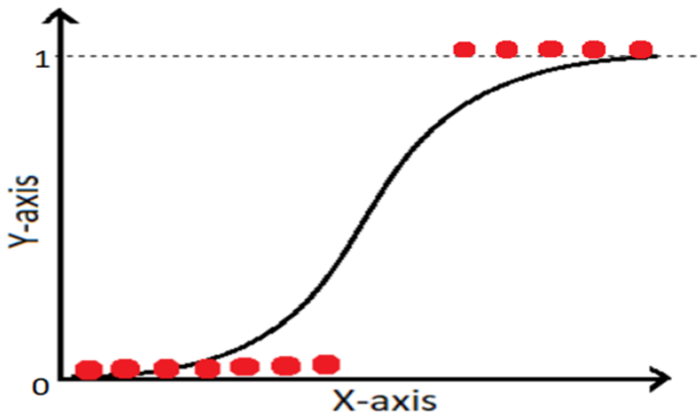

Figure 3.1: Showing Logistic Regression S-Shaped Curve (Khushwant Rai)

Assume we just know a person's height and want to predict whether they are male or female. We can discuss either the likelihood or the odds of being male or female. Assume that the likelihood of being male at a particular height is 90. Then the odds of being male are

$$Odds = \frac{P}{1 - P} \quad (3.7)$$

The logistic regression model is based on the odds of a two-level outcome of interest (LaValley, 2008). For the sake of simplicity, I'll assume that we've selected one of the result levels as the event of interest and refer to it simply as the event. The event's odds are calculated as the ratio of the probability of the event occurring to the probability of the event not occurring. Odds are commonly employed in gambling, with "even odds" (odds=1) indicating that the event will occur half of the time (Fulton et al., 2012).

ii) PHP MySQL (Web-Based System):

PHP, as a programming language, is popular among web developers due to its ability to communicate with databases such as Oracle and MySQL. PHP (or PHP Hypertext Pre-processor) is a server-side scripting language that allows you to construct dynamic web pages that interact with databases (Greenspan and Bulger, 2001). It is a widely used open source language designed primarily for online application development and can be incorporated in HTM (Conallen, 2003).

i. **User Interaction:** PHP is a server-side scripting language commonly used for web development. Integrating PHP with MySQL allows for the creation of an interactive web-based system where users can input data and receive dynamic predictions based on the logistic regression model.

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ii. **Database Management:** MySQL is used to store and manage data related to the dynamic frequency reuse strategies. It allows efficient retrieval and storage of information, enabling real-time decision-making.
iii. **Scalability:** PHP and MySQL are known for their scalability, making them suitable for handling large datasets and accommodating potential future expansions of the dynamic frequency reuse system.

iii) Poisson (Queuing) Theory:

The M/M/1 system consists of a Poisson arrival (Arrival rate l), a single exponential server (Service rate m), an unlimited FIFO (or not defined queue), and an unlimited client base (Dudin et al., 2020). Because both arrival and service are Poisson processes, it is possible to determine the probability of various system states required to compute the quantitative parameters. The system state refers to the number of clients in the system. It could be any nonnegative integer number.

The notation "M/M/1" denotes a queuing system model that is widely used in queueing theory (Sundari and Palaniammal, (2015). Each "M" in the notation denotes a distinct feature of the system:

i. **Arrival Process (M):** The first "M" stands for the probability distribution of the inter-arrival times of customers or entities entering the system. "M" typically stands for memoryless, which means that the time between arrivals follows an exponential distribution. This is also known as a Poisson arrival process.
ii. **Service Process (M):** The second "M" represents the probability distribution of service times. Like the arrival process, "M" often denotes memoryless service, following an exponential distribution. Each customer is served independently of others, and the service rate is constant.
iii. **Number of Servers (1):** The "1" indicates that there is only one server available to serve customers. In M/M/1, there is a single queue and a single server.

Poisson theory is often used to model the distribution of events over a fixed interval of time or space. In the context of dynamic frequency reuse, Poisson theory was used to predict and model the occurrence of events related to frequency resource utilization. It complement the logistic regression approach by providing a statistical framework for understanding the distribution of events, especially around the decision to switch between reuse strategies is influenced by factors related to event occurrence. It also offered insights into optimizing resource allocation by providing a probabilistic perspective on the occurrence of interference events.

Queuing theory is a mathematical theory that uses a variety of mathematical notations. The table below lists a few of the basic notations utilized in the calculations for this research queuing model.

NOTATION	DESCRIPTION
λ	Arrival Rate
μ	Service Rate
Lq	Average number of customers waiting for service
L	Average number of customers in the system (waiting or being served)
Wq	Average time customers wait in queue
Ws	Average time customers spend in the system
ρ	System Utilization

In this study, we chose three waiters (Servers) to act as bank attendants, serving customers upon their entrance in the banking hall. The study found that new customers approach the counter every ½ minutes during the busiest hours of 9:30am to 10:45am, based on an 8-hour banking workday.

3. Research Methodology

In this section, the strategy that was used in this research to achieve the objectives that were given is explained in detail. Using a frequency reuse scheme of a defined logistic algorithm, the approach involves optimizing the available spectrum in order

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to dynamically change the reuse factor from three (RF-3) to seven (RF-7) in order to increase the capacity of the network to accommodate more users, reduce congestion and interference within a cell, and increase the number of users who can be accommodated. The establishment of appropriate parameters and tools for frequency reuse is the method that is being taken here. These parameters are designed to enhance the performance of the network in terms of congestion and interference. Within the context of a dynamic and densely populated wireless environment, the purpose of this study is to solve the issues that are connected with maximizing spectral efficiency, controlling interference, and establishing connection fairness among users.

Below are the conditions and process of switching:

This methodology combines the power of PHP for real-time data processing and database management with machine learning and queuing theory for a comprehensive dynamic frequency reuse scheme in the 5G spectrum management context.

1. Database Schema Design:

Create a MySQL database to store relevant information, including network data, user classifications, and queuing parameters.

Design tables for historical data, current network conditions, user information, and queuing details.

2. Data Collection and Processing:

Implement PHP scripts to collect and process real-time data, such as user distribution, interference levels, and traffic patterns.

Store processed data in the MySQL database for analysis.

3. Feature Selection and Data Pre-processing:

Identify relevant features for the Logistic Regression model, such as historical usage patterns, interference levels, and user classifications.

Use PHP scripts to pre-process the data, normalizing and cleaning it for training the model.

4. Logistic Regression Model Training:

Utilize PHP scripts to split the dataset into training and validation sets.

Implement Logistic Regression training using a machine learning library in Python. Use the trained model to predict the optimal time for transitioning.

5. Integration with Queuing Theory:

Develop PHP functions to implement queuing models based on the waiting times for users beyond the capacity of reuse-7.

Map queuing parameters to features used by the Logistic Regression model for a seamless integration.

6. Transition Threshold Determination:

Implement PHP scripts to dynamically determine transition thresholds based on Logistic Regression predictions, considering user classifications and queuing insights.

7. Real-time Monitoring and Prediction:

Develop a PHP-based real-time monitoring system that continuously fetches data from the MySQL database.

Integrate the trained Logistic Regression model into PHP scripts for making predictions on the optimal time to transition.

Utilize queuing theory implemented in PHP to dynamically adjust transition decisions based on current network conditions and waiting times.

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8. User Classification and Queuing Management:

Implement PHP scripts to continuously classify users based on their current category (reuse-3, reuse-7, or queued).

Manage the queuing system using PHP functions, ensuring fair and efficient allocation of resources when space becomes available.

9. Transition Execution:

Develop PHP scripts to execute the switch from reuse-3 to reuse-7 when the Logistic Regression model and queuing parameters jointly signal the need for a transition. Ensure coordinated transition across cells to minimize disruptions and optimize spectral efficiency.

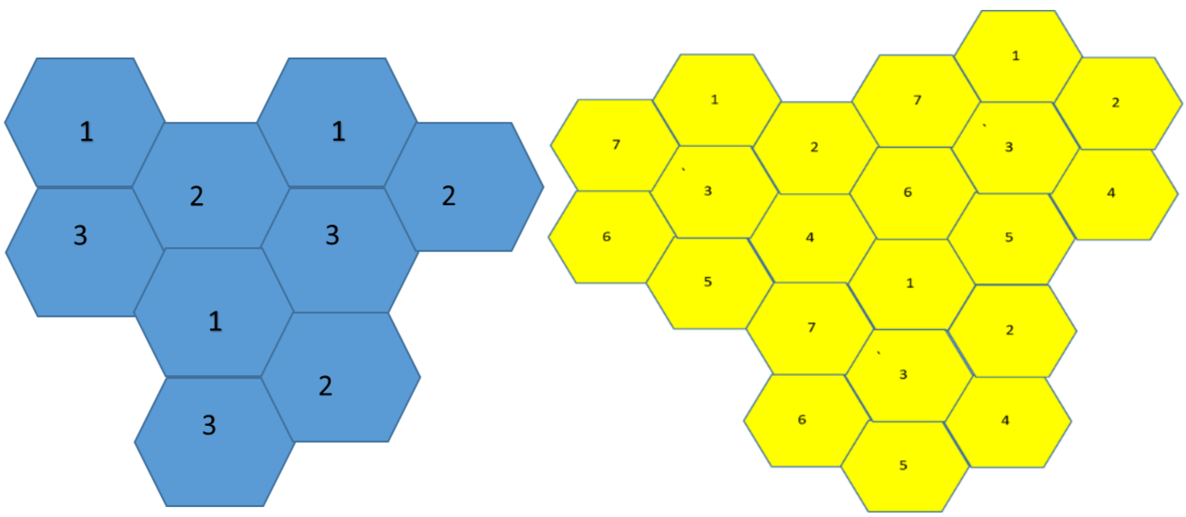
10. Performance Evaluation and Feedback Loop:

Create PHP scripts to evaluate the performance of the dynamic frequency reuse scheme, calculating metrics such as spectral efficiency, interference levels, and user satisfaction. Establish a feedback loop in PHP to update the Logistic Regression model and queuing parameters based on ongoing network data, ensuring adaptability to evolving conditions.

11. Simulation, Testing, Deployment, and Optimization:

Conduct simulations and testing scenarios using PHP scripts to validate the effectiveness and robustness of the integrated methodology. Deploy the dynamic frequency reuse scheme in a PHP/MySQL environment, gradually expanding its implementation to a larger network.

Optimize the PHP scripts based on real-world performance feedback, continuously refining the Logistic Regression model and queuing parameters.



Cluster 3 **Cluster 7**

Calculating the Cluster Size:

Using $N = i^2 + ij + j^2$

if i=1, j=1

$N = 1^2 + 1x1 + 1^2 = 3$,

if i=1, j=2

$N = 1^2 + 1X2 + 2^2 = 1+2+4 = 7$

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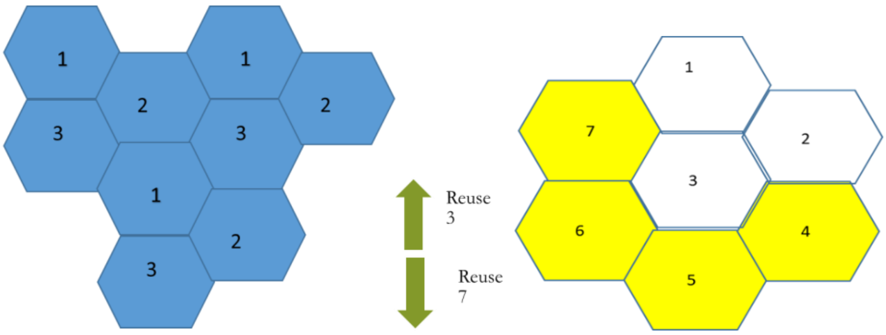
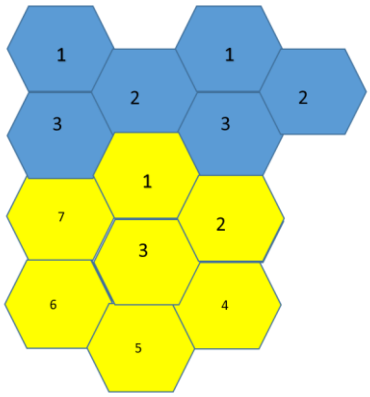
Dynamic Switching from Reuse Factor 3 and 7



Configured Reuse 3 **Configured Reuse 7**



Overlay of Reuse 3 and Reuse 7

Within the scope of this simulation, the following tools were used to achieve the results:

i. PHP AI Framework
ii. jQuery UI
iii. Chartist JavaScript Frame work
iv. Bootstrap framework
v. Mysqul Database
vi. Queuing Theory (Poisson)
vii. Reuse factor of 7 (RF-7) and reuse factor of 3 (RF-3) configurations.

The integration of logistic regression into a web-based system using PHP and MySQL involves implementing the logistic regression model within the server-side PHP code, establishing a connection to the MySQL database to manage data, and using these technologies to deliver predictions or insights through a web interface.

Below is a description of the technique that was used up to this point in the work: We developed a simulation environment by using unique PHP MSQL and Logistic regression algorithm in machine learning. This allowed us to carry out an exhaustive examination. The significance of using Logistic Regression, PHP MySQL, and Poisson theory in the methodology for dynamic frequency reuse strategy switching from Reuse 3 to Reuse 7 can be discussed in terms of their specific roles and contributions to the research.

The odds in logistic regression were used in this research work, which represent the ratio of the probability of an event occurring to the probability of it not occurring. The odds can be expressed as:

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$$Odds = \frac{p}{1-p} \qquad (3.1)$$

Here,

P= is the probability of the event occurring,

1−p is the probability of the event not occurring.

In logistic regression, the relationship between the predictor variables X and the log-odds of the event occurring is modeled using the logistic function. The logistic function is defined as:

$$logit(p) = \ln\left(\frac{p}{1-p}\right)\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n \qquad (3.2)$$

$Logit(p) = is\ the\ natural\ logarithm\ of\ the\ odds$

P = is the probability of the event occurring.

$\beta_{0,}\beta_1, \beta_{2,\ldots\ldots}\beta_n$ = are the regression coefficients.

$X_1, X_{2,\ldots\ldots}X_n$ = are the predictor variables.

To find the odds from the logistic regression model, you can exponentiate the log-odds:

$$Odd = e^{logit\ (p)} + e^{(\beta\_0+\beta\_1\ X\_1+\beta\_2\ X\_2+\cdots+\beta\_n\ X\_n\ )} \qquad (3.3)$$

Modelling using Logistic Regression:

$$ODD(LR) = \left(\frac{P}{1-P}\right) \qquad (3.8)$$

$$MORNING = \left(\frac{R3}{R7}\right) \qquad (3.9)$$

Assumption:

R3_Data=70

R7_Data=22

Sum_R3_R7 = R3_Data + R7_Data (3.10)

$$\text{Probability}_{\text{R3}} = \frac{R3\_Data}{sum\_R3\_Data\_R7\_Data} = 0.76 \qquad (3.11)$$

$$\text{Probability}_{\text{R7}} = \frac{R7\_Data}{sum\_R3Data\_R7\_Data} = 0.23 \qquad (3.12)$$

Using the model Odds:

$$LR_{R3} = \frac{P\_R3}{1-P\_R3} = 3.1 \qquad (3.13)$$

$$LR_{R3} = \frac{0.76}{1-0.76} = 3.1$$

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$$LR_{R7} = \frac{P\_R7}{1 - P\_R7} = 0.29 \quad (3.14)$$

$$LR_{R7} = \frac{0.23}{1 - 0.23} = 0.29$$

%Performance(R7):

$$\%Value = \frac{LR_{R7}}{LR_{R3} + LR_{R7}} \quad (3.15)$$

$$\%Performance = \%value * 100 \quad (3.16)$$

%Performance= 8.55%

Assume a Poisson arrival distribution with a mean rate of lambda = 0.5 customers per minute (that is, one client appears every 1 / lambda = 1/0.5 = 2 minutes) and a service time distribution with a mean service rate of 4 customers per minute. The following results were achieved using a Simple M/M Queue System with a single server.

Inputs:

Service rate: μ = 4 customers / minute
Arrival rate: λ = 0.5 customers /minute
Number of server = 1

Using the M/M/1 model, we get the following results:

Average Server Utilization (ρ) = $\frac{\lambda}{\mu} = \frac{0.5}{4}$ = **0.125** (3.17)

Average Number in the Queue (**Lq**) $\frac{\rho 2}{(1-\rho)} = \frac{0.016}{0.875}$ = **0.0182** (3.18)

Average Number in the System (L) $\frac{\rho}{(1-\rho)} = \frac{0.125}{0.875}$ = **0.143** (3.19)

Average Time in the Queue (**Wq**) $\frac{\rho}{\mu(1-\rho)} = \frac{0.125}{4*0.875}$ **= 0.0357 = 60*0.0357 = 2.142 min** (3.20)

Average Time in the System (Ws) = $\frac{L}{\lambda} = \frac{0.143}{0.5}$ = **0.286** (3.21)

For more than one Server, Average Server Utilization (ρ) = $\frac{\lambda}{n\mu}$ (3.22)

*Where n (**1, 2, 3…n (servers)**)*

Below is the summary of the above solution in table 3.3

S/N	DESCRIPTION	RESULT VALUE	TIME(PER MIN)
1	Average Server Utilization	0.125	-
2	Average Number in the Queue	0.0182	-

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3	Average Number in the System	0.143	-
4	Average Time in the Queue	0.0357	2.142
5	Average Time in the System (Ws)	0.286	17.16

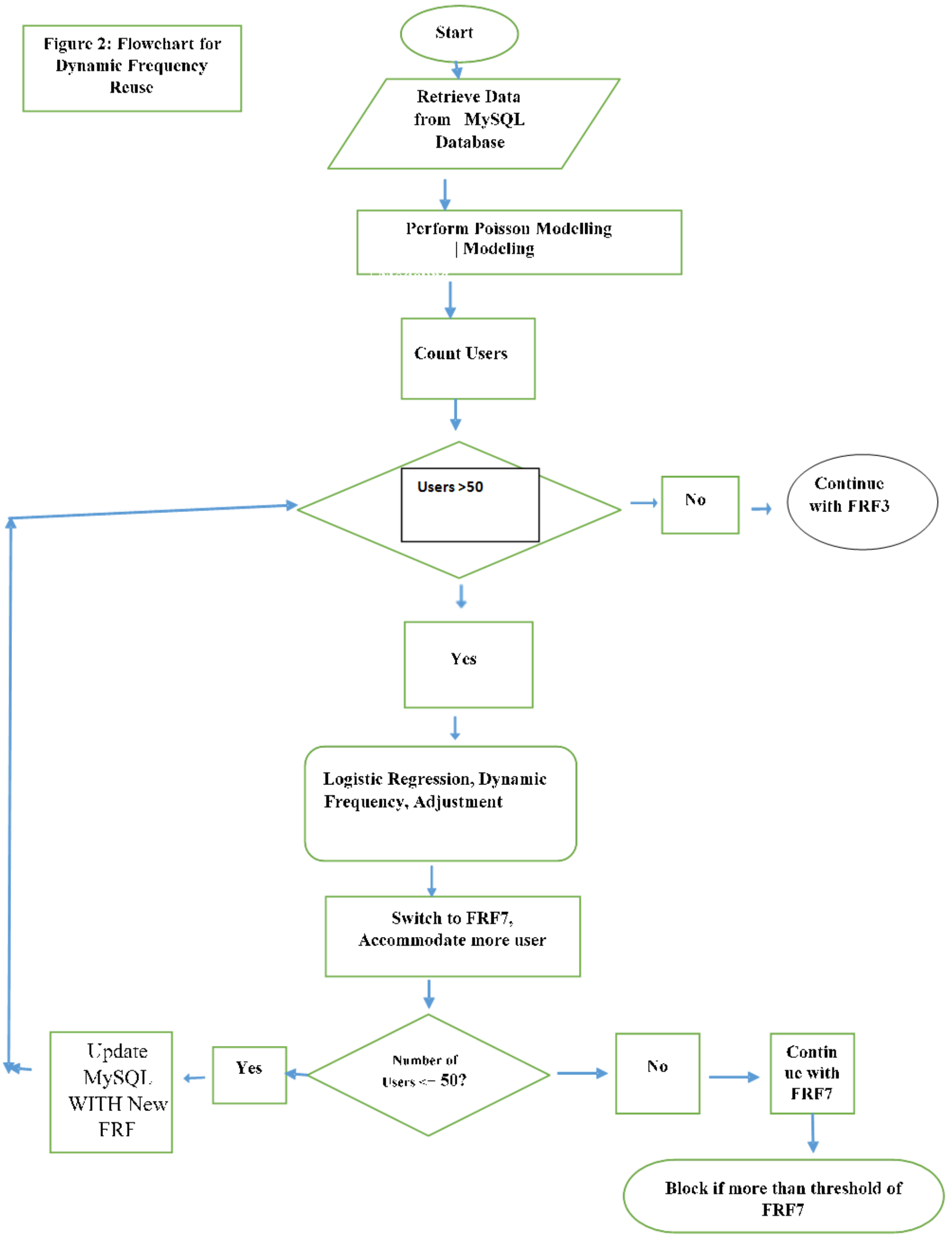

Figure 2: Flowchart for Dynamic Frequency Reuse

Initial State - Reuse Factor 3, System Status Unsatisfied (1-50 users):

In this state, the system is designed to handle up to 50 users with a reuse factor of 3, but the current demand is not being met, leading to an "unsatisfied" system status.

Transition to Reuse Factor 7, System Status Allocated (51-65 users):

As the user load increases beyond the capacity of the Reuse Factor 3 system (more than 50 users), the dynamic switching process is triggered. The system switches to a higher reuse factor, in this case, a reuse factor of 7, to accommodate a larger number of users (from 51 to 65 users).

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This transition aims to allocate resources more efficiently and improve system performance to meet the increased demand.

Congested State - Users on Queue (67 and above):

If the user load continues to grow and surpasses the capacity of the Reuse Factor 7 system (67 users and above), the system enters a congested state. Users beyond the system's capacity are placed in a queue, waiting to be attended to.

3.1 Sources of Data

The information included in this report was obtained from the control room of a mobile telecommunications Servicing company in Nigeria. For the purpose of expanding the capacity of the network to accommodate users and avoiding congestion within a cell, our primary emphasis is on the efficient optimization of the available spectrum via the use of a frequency reuse scheme of a predetermined algorithm. This is done in order to dynamically adjust the reuse factor of the network inside the network. The Table provides a summary of the statistical mean of the primary indicators that were obtained from various data sources over the course of 3 weeks. Figure displays the traffic graphs that corresponds to the data that was provided. In addition, synthetic data generation method was to supplement the limited real-world data available for this research to ensure robust analysis or model training.

Table 1: Number of users

#	Site	Service Rate	Cell User	Cell Status	Blocked	Drop User	Day Status
1	AKS-LRV0523A	40	40	0	0	0	Morning
2	AKS-LRV0523A	15	15	0	0	0	Morning
3	AKS-LRV0523A	3	3	0	0	0	Morning
4	AKS-LRV0523A	42	42	0	0	0	Morning
5	AKS-LRV0523A	9	9	0	0	0	Morning
6	AKS-LRV0523A	50	50	0	0	0	Morning

Table 2: 5G Dataset

nrCarrierGroupId	nrPhysicalCellDUId	NR RAN UE Throughput DL(Kbps)	Average number of NSA UEs with RRC connections	0.35	0.3145223	Congestion from throughput	Congestion from Average Ues	Congestion Label
1	101	80,932.63	3.0199	0.14011542	0.0791522	0	0	0
2	102	152,709.59	1.1289	0.26437999	0.0295887	0	0	0
3	103	163,225.4	5.8882	0.28258559	0.1543308	0	0	0
1	101	394,427.19	3.9833	0.68285597	0.104403	1	0	1
2	102		0.0000	0	0	0	0	0
3	103	312,409.67	4.7364	0.54086233	0.1241419	1	0	1
1	101	142,448.03	16.3367	0.24661456	0.428188	0	1	1
2	102	103,322.84	12.2889	0.17887869	0.3220944	0	1	1

4. Results and Analysis

User Accommodation Analysis:

1. Before Switching to Reuse-7 (Reuse-3 Phase):

In the initial phase operating under the reuse-3 pattern, the system is designed to accommodate users up to a certain threshold, often set at 50 users. Each cell within the network is assigned a specific set of frequency channels, and these channels are reused every three cells to minimize interference. Users are distributed across the cells according to the reuse-3 pattern,

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ensuring that the same frequency channels are not allocated to adjacent cells. The network capacity is effectively managed within this reuse-3 configuration. The system reaches its defined capacity when the number of users exceeds the predetermined threshold (e.g., 50 users). At this point, a queuing mechanism is triggered, signaling to the logistic regression model of the need for a more aggressive frequency reuse strategy. This triggered the dynamic switch from reuse 3 to reuse 7.

2. After Switching to Reuse-7 (Dynamic Phase):

Upon recognizing the increased demand for network resources, the system dynamically switches to a reuse-7 pattern to enhance user accommodation. In the reuse-7 configuration, the same frequency channels are now reused every seven cells, allowing for a more aggressive frequency reuse pattern. This results in an expanded user range, accommodating users from 51 to 65 within the same set of channels. The transition to reuse-7 not only accommodates more users but also contributes to improved spectral efficiency, as channels are reused more aggressively. We can see in below figure 4.1 the reuse 7 percentage performance of 27.55%. The same details are also reflected in the figures 4.2 and 4.3 below. The Logistic Regression model plays a pivotal role in predicting optimal times for transitioning from reuse-3 to reuse-7.

Users beyond the capacity of reuse-7 (e.g., users 66 and above) are directed to a queuing system. Queued users patiently wait for an available channel, and the queuing theory principles guide the fair allocation of resources.

Significance of User Accommodation Analysis:

The dynamic switching mechanism significantly increases the overall capacity of the network by transitioning from a more conservative reuse-3 pattern to a more aggressive reuse-7 pattern. This accommodates a larger number of users within the existing frequency spectrum. The analysis demonstrates the effectiveness of the system in adapting to changing demand, ensuring that frequency resources are optimally utilized the queuing system efficiently manages users beyond the capacity of reuse-7, minimizing the impact of waiting times and ensuring a systematic allocation of channels. Spectral efficiency is measured as the number of users accommodated per unit of frequency spectrum. Post-switch to reuse-7, there is a notable increase in spectral efficiency due to the more aggressive frequency reuse pattern.

Performance Analytics

Technique	Morning	Afternoon	Evening
Logistics Regression	2 / 0.5	2.27 / 0.44	1.62 / 0.62
RF7 Percentage Performance	20%	16.26%	27.55%

Resource Utilization More in the Evening
27.55

Figure 4.1: Show Performance Analytics of Reuse Factor 7 percentage Performance

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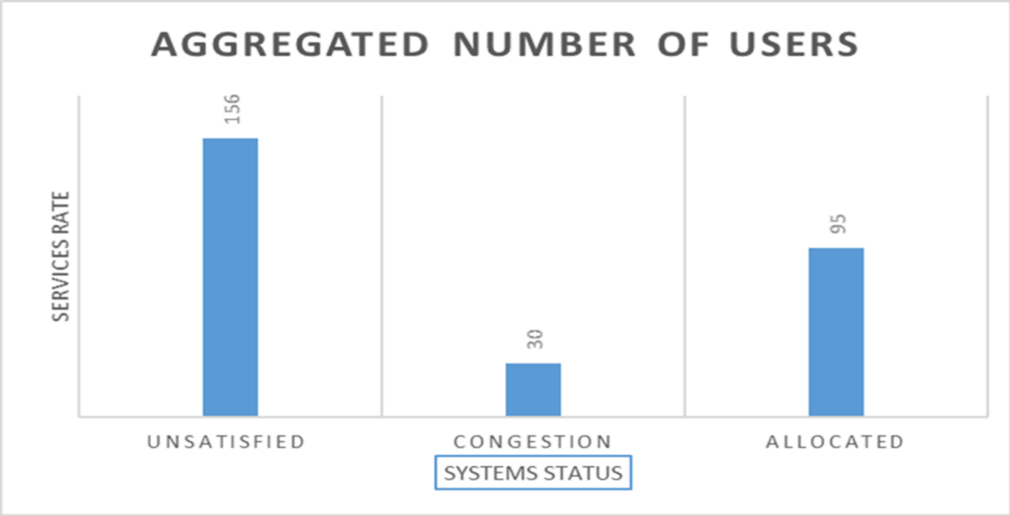

Figure 4.2 Showing number of users at RF3 (Unsatisfied) RF 7 (Allocated) and Congested

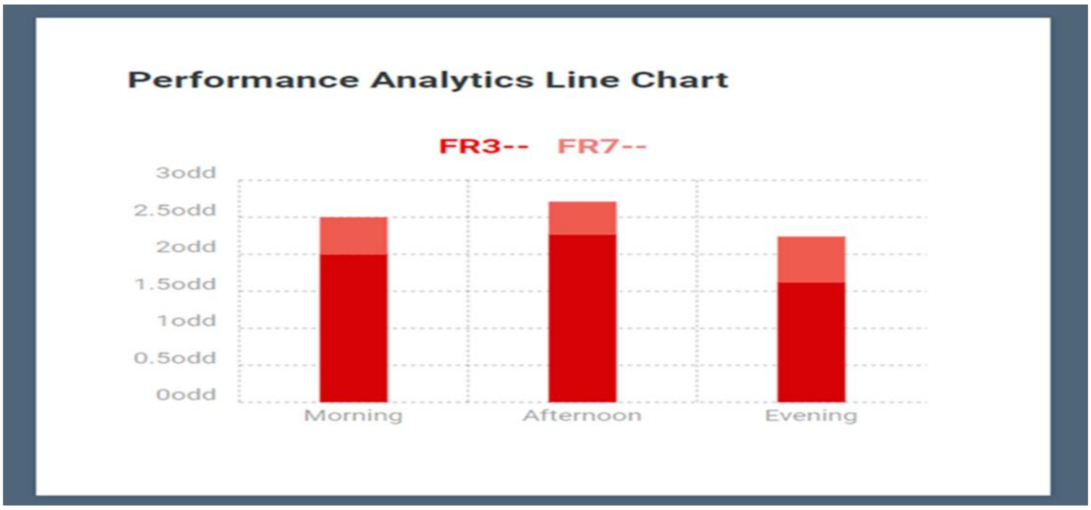

Figure 4.3: Showing the Bar Chart of RF3 and RF7 Using the Odd Ratio

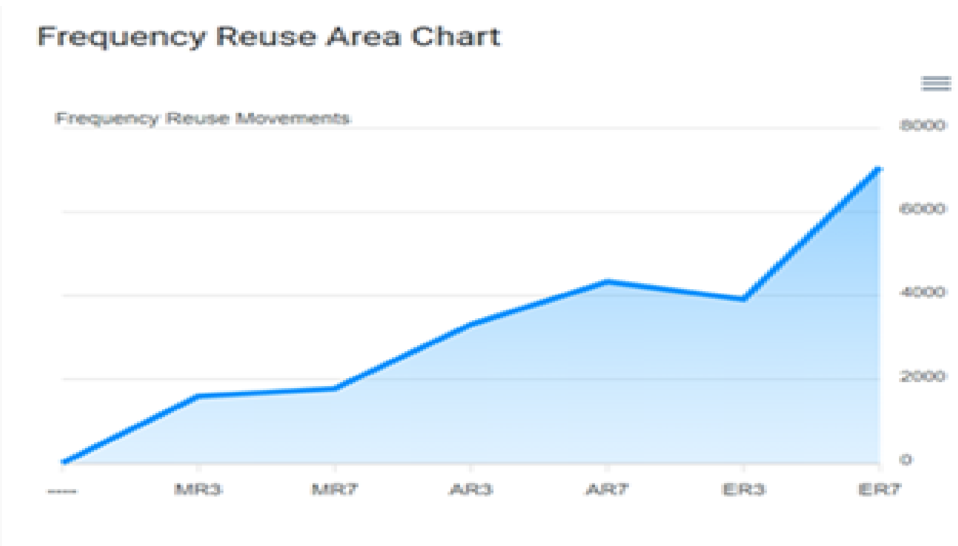

Figure 4.4 Frequency Reuse Area Chart for FR3 and RF7

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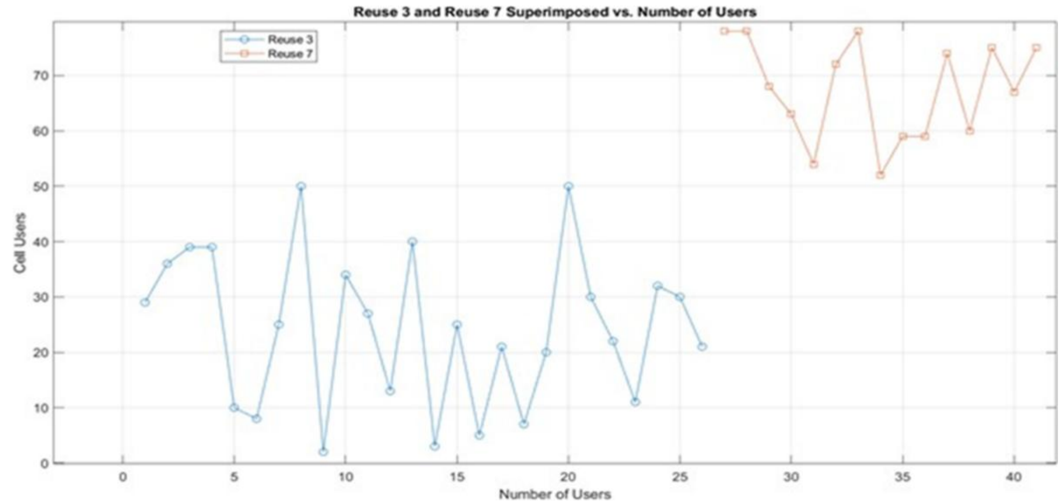

Figure 4.5: Graph showing the Switch from RF3 to RF 7 as the Users increase

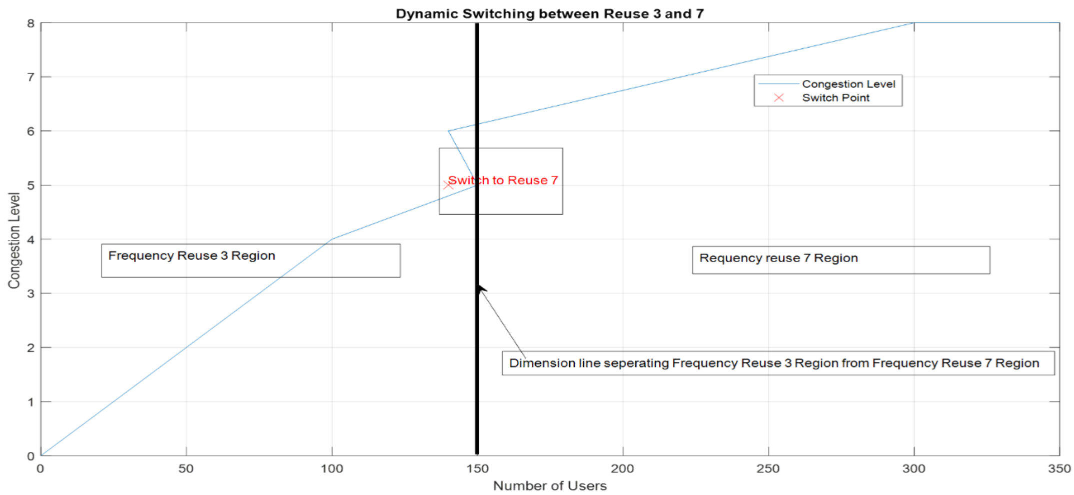

Figure 4.5: Showing the Dynamic Switching from RF3 to RF7

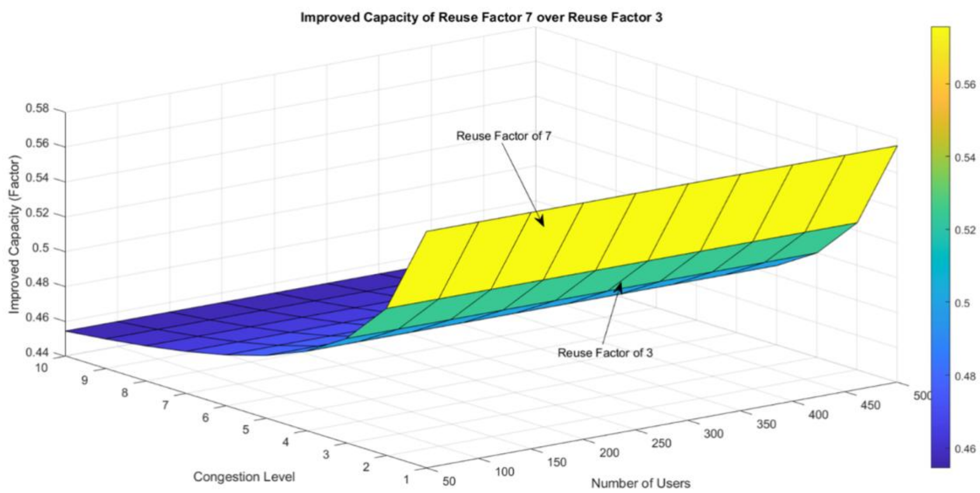

Figure 4.6: Showing the Improved capacity of the system

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4.2 Discussion of Findings

The graph represents the number of users in the cellular network in different scenarios referring to Figure 4.4, Figure 4.5 and Figure 4.6. They started with a baseline where the number of users is relatively low. The area of concern is the representation of the frequency reuse pattern, with two distinct values: RF3 and RF7.

Initially, the graph line starts at RF3, indicating that the network operates under the reuse-3 pattern when the number of users is below the switching threshold. As the number of users increases, set a threshold value (e.g., 51 users) that triggers the switch from RF3 to RF7. At this point, we introduce a vertical line or a marked point on the graph Figure 4.5 to signify the transition. After crossing the threshold, the graph line transitions to RF7, indicating that the frequency reuse pattern has switched to a more aggressive reuse-7 configuration. Beyond the threshold, the graph line remains at RF7, showcasing that the network continues to operate under the reuse-7 pattern. The graph may continue to depict additional thresholds as it switches between reuse 3 and reuse 7 as the system dynamically adapts to varying user loads. As the number of user's increases, the graph visually represents how the network adapts its frequency reuse pattern. The switching threshold acts as a trigger point, indicating when the system transitions from RF3 to RF7. The graphs effectively communicate the dynamic nature of the frequency reuse scheme, showcasing the system's ability to adapt to changing conditions.

5. Conclusion

In conclusion, the implementation of a dynamic frequency reuse scheme incorporating a Logistic Regression model and Queuing Theory has proven to be a pivotal strategy for enhancing 5G spectrum management. The scheme seamlessly transitions from a conservative reuse-3 pattern to a more aggressive reuse-7 configuration when the number of users exceeds 50, demonstrating adaptability to evolving network conditions. The dynamic switching mechanism effectively accommodates a larger number of users by transitioning from reuse-3 to reuse-7. Users ranging from 51 to 65 are accommodated within the reuse-7 configuration, leading to a significant increase in network capacity. The transition to reuse-7 contributes to enhanced spectral efficiency by allowing for more aggressive frequency reuse. Spectral resources are utilized more efficiently, resulting in a better balance between capacity and interference management. The introduction of a queuing system for users beyond 65 ensures fair resource allocation and systematic channel assignment. Queued users experience managed wait times, minimizing the impact on user experience. The Logistic Regression model plays a crucial role in predicting optimal times for transitioning from reuse-3 to reuse-7.The model's performance directly influences the dynamic adaptability of the system to changing user demands. The dynamic frequency reuse scheme successfully maintains a balance between increased user accommodation and maintaining a high quality of service. Continuous monitoring ensures that the system adapts to varying network conditions while optimizing user experience. The scheme showcases the importance of adaptive network management strategies, responding to real-time user demands and traffic patterns. Machine learning-driven decision-making, coupled with queuing theory principles, enables a dynamic and responsive network.

Future Considerations and Research area:

1) Continuous optimization efforts and model refinements are imperative for sustained performance improvements.
2) As 5G networks evolve, the scheme should adapt to emerging technologies and changing user behaviors.
3) Consider the dynamic switch of the entire network to mitigate network disruption.

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