

## **Chapter One**

### **Introduction**

#### **1.1 Background to the Study**

Nations must remain committed to investing in their telecommunications systems in order to keep up with the increasing demands of their customers i.e. they must meet the growing demands of their customers through technological advancements, data traffic growth, mobile connectivity, global competitiveness and the quality of life. However, their current networks are unable to expand at the desired rate, leading to a decline in the quantity and quality of calls users are receiving. This phenomenon is referred to as "call drop" and is typically caused by a call terminating due to technical difficulties before the subscriber is able to complete their conversation or upon one of them terminating the call. Traffic Channels (TCHs) created and allocated by incoming and outgoing calls that have not yet been blocked or terminated by a service provider are frequently the subject of prior termination complaints from users<sup>1</sup>. Telecommunication service providers experience network outages on a regular basis, which can have a negative impact on their reputation in addition to other problems such as call drops or poor call quality. As a result, mobile phone subscribers are increasingly concerned about the image and reputation of telecommunications service providers.

A call drop is an unexpected interruption of a user's conversation that results in the connection abruptly breaking off. This can significantly affect the functioning of the service and the user experience in urban and rural settings. The quality and quantity of a call can be affected by the digital divide, as it can be difficult to transfer a call to a neighbour on-time. The call drop procedure, in which calls are disconnected while subscribers are speaking, could result in calls being dropped immediately. Call losses can be caused by a variety of factors, such as signal reception, propagation, or user behaviour. As neighbouring and

immediate calls exist, it is necessary to transfer a call between two devices if the call fails. This can result in a decrease in service quality and a degradation of the telecommunications network. One of the primary causes of call losses is the QoS index, which is used to monitor mobile network performance. Telecommunications service providers use various optimization techniques to reduce call losses on a range of services, such as increasing network usage and service coverage areas, increasing the likelihood of congested and interference and attempting to use traffic balancing across multiple frequencies<sup>3</sup>. Call drop is a phenomenon that can be attributed to a variety of factors, such as radio interference between adjacent calls, inadequate radio reception, antenna problems, network performance problems, wireless network overcapacity, excessive cell demands, unauthorized repeaters and transmission media. The frequency of dropped calls can vary depending on the mobile device. This can have a negative impact on subscribers, especially when QoS is weak. In order to achieve their objectives, telecom operators should focus on reducing the rate of drop calls and also consider the success rate. Telecom operators should aim to reduce the number of dropped calls rather than eliminate them due to cost, as this will help address customer dissatisfaction<sup>4</sup>. As the focus is on quality of calls, it is important for network providers to find ways to reduce churn rate. To ensure reliable voice call service, it is essential for operators to configure services to provide high-quality calls<sup>5</sup>. Telecommunication service providers need to invest a significant amount of time, money, and effort to improve and optimize their operational services on a daily basis. Telecommunication service providers must invest a considerable amount of time, resources, and expertise to optimize and enhance their operational services daily. As a result of the vast amount of network traffic, security issues must be addressed. Apart from the statistical techniques used to anticipate the calls in mobile communications, the utilization of machine learning techniques may be one of the

potential methods to enhance the quality of calls, reduce congestion, and improve the customer experience<sup>6</sup>.

Telecommunications companies have begun to invest in and evaluate machine learning algorithms for both operational and commercial networks<sup>6</sup>. Machine learning technologies are utilized to analyse and classify subscribers' call detail records and to identify unusual traffic patterns. Furthermore, machine learning techniques are necessary for the prediction of suspicious calls by subscribers and the detection of cluster issues by telecom companies. By collecting a variety of data sources, including subscriber-specific information, customer profile data, caller behaviour data, demographic data and network data from telecommunications sectors, it has been possible to gain insight into a subscriber's decision-making process when it comes to continuing to use their services or switching to another service provider<sup>7, 8</sup>. This approach implies that the implementation of machine learning-based applications by telecommunications network providers will have a direct impact on the performance of their customer calls. Furthermore, call drop poses a significant challenge to mobile communication services, as it increases the demand on the network, resulting in a decrease in operators' revenue and an increase in network congestion<sup>9</sup>. When capacity augmentation is delayed, it can lead to a serious network issue, as network congestion can lead to call dropout and poor Quality of Service (QoS) due to the fact that it can occur from any location<sup>10, 11</sup>. To reduce network congestion, many researchers have employed call drop methods. Mobile communication networks have become more efficient over time, resulting in fewer subscribers having to share the network resources with a larger number of users<sup>12</sup>. Other factors that can contribute to network congestion include call dropout and unsuccessful handover, as well as network failure, which occurs when the exchange of hardware system resources is not sufficient to meet the needs of the network users<sup>13</sup>. Predicting this network congestion is essential for improving the network security and network speed<sup>14</sup>.

This study outlines a range of machine learning algorithms used for data analysis. It is anticipated that predictive analysis of cellular network congestions will be a key element in the next generation of mobile networks. By anticipating user needs, the system can allocate resources effectively. It is difficult to predict cellular network data flow accurately for enhanced network management.

## **1.2 Statement of the Problem**

Lagos has the most Mobile infrastructure and services, such as cell sites, data services, etc., of any Nigerian metropolis and has the most mobile customers of any Nigerian capital. Numerous calls are dropped and the call setup success rate is also poor. Although the call setup rate is generally low, there are moments when you want to call<sup>15, 16 17</sup>. Among these services, cellular mobile service is where customers most frequently complain about the quality of the provided services. Despite the company's outstanding success in creating a cutting-edge information and communications technology network architecture, users have been criticizing the poor quality of mobile service. The accessibility of Mobile services in Lagos is of paramount importance, particularly during the rainy season when traffic congestion is prevalent. Lagos State has a large population of mobile users, which may be subject to the limited number of errors permitted by mobile providers. If a successful call is not possible due to congestion, then the call will be terminated. Mobile service is one of the services clients most frequently complain about<sup>18</sup>.

A study to evaluate the performance of multi-layered perception neural networks (MNNs) was conducted<sup>19</sup>. The results of the study revealed that a MNN model with 15 layers of hidden neurons, a training algorithm with the Adam optimizer, and an activation function with Relu resulted in a mean absolute error (MAE) of 0.272. On the other hand, a model consisting of 10 layers of discrete neurons with identical activation functions and training algorithm yielded an average MAE (0.345). Machine learning model is aimed in enhancing

the call quality prediction of telecom service providers<sup>20</sup>. To address the issue of call drop, a neural network model was employed to improve call performance and efficacy. A machine learning algorithm, the Random Forest Classifier, was used in the study, which was conducted with Python software. The call parameters that were used in the study were Call Data, Call Rating, Subscriber Count, and Call Drop Category. The primary objective of the study was to create a model that could accurately predict call parameters in the present moment and provide an average call rank when a call was completed. The study duration was limited to three months. The results of the study revealed a variety of performance indicators, including 90% accuracy, 93% precision, 89% recall, 92% recall, 98% F-score, and 88% call quality. The report recommends that telecommunications companies use machine learning techniques to reduce call drops and repair them, thus increasing the quality of subscribers' calls in the future and facilitating continuous discussion. The report suggests that telecom service providers should construct their networks and enhance security to reduce call drops within their network.

It is our understanding that no research has been conducted to improve call quality for call drop minimization during handover based on some telecommunications network data using Long Short Term Memory (LSTM), Convolutional Neural Network (CNN) and Ensemble Models to minimize call drop and solve them in order to improve the quality of subscriber calls for continuous communication in the future.

### **1.3 Justification of the Study**

The main technical challenges associated with the increase in network traffic relate to the use of network assets, the use of resources, and the expenses associated with the installation of equipment. This thesis is based on extensive research on how to optimise the performance and efficiency of network resources while maintaining QoS. Network expansion is an approach that can be implemented cost-effectively. Network operators typically increase

capacity when the subscriber base increases significantly. The thesis is used as a reference for the development of a queuing call methodology and the utilization of machine learning techniques to reduce call drop.

#### **1.4 Aim and Objectives of the Study**

The aim of this project is to improve call quality for call drop during handover in mobile communications. The specific objectives of this study are to:

- i. preprocess the real and simulated datasets
- ii. develop an ensemble model (LSTM and CNN)
- iii. evaluate the model's performance using some standard benchmarks.

#### **1.5 Research Questions**

1. What machine learning techniques are best suited for predicting network congestion and queuing of call drop during handover in mobile communications?
2. What accuracy can the neural network predict using the provided dataset?
3. Which attributes are most useful for identifying and classifying the model used for predicting network congestion for queuing of call drop during handover in mobile communications?

#### **1.6 Significance of the Study**

When utilizing queuing models for communication, subscribers frequently experience poor quality of service in call drop; this can be annoying when users can't communicate well. Most people find it difficult to think effectively while on the phone and when there is an echo. The caller is even more irate because they invested their money, time, effort, and energy without receiving anything in return. Voice messages that are not correctly heard, relayed, or understood may irritate people. Given the requirement for call quality, it doesn't matter

whether there is poor communication. This study aims to decrease the likelihood of low calls and raise service quality. A unified communication system that enables users to communicate with one another, such as through phones, laptops or tablets can help to reduce communication costs and improve signal clarity. This thesis aims to identify the optimal metrics for queueing of call drops during handover within mobile communications by predicting the network congestion.

### **1.7 Scope of the Study**

The scope of this study will be Lagos State, Nigeria because it is the Nigeria's commercial capital and has the most mobile users of any Nigerian city. This thesis will compile simulated data over a month period. The study utilizes a dataset with a total of 3000 data points across 30 cell towers and the period is between the 1<sup>st</sup> to 10<sup>th</sup> of July, 2023 and with each cell running for five (5) minutes. This research made use of ensemble algorithms to reduce the congestion of call drops in wireless network. Top-performing Long Short Term Memory and Convolutional Neural Network models were selected and their predictions were combined using a weighted average ensemble approach. Performance evaluation of the model is evaluated and compared and the result of the Ensemble model was compared with the conventional LSTM and CNN.

### **1.8 Limitation of the Study**

The process of obtaining datasets from all network providers in Nigeria proved to be challenging. The time and resources required to extract, pre-process, analyze, and evaluate the datasets necessitated the simulation of the dataset. As a result, the analysis of the dataset is limited to a period of one month, utilizing three classification algorithms. Despite the impressive results of the system, the research revealed several limitations and areas for improvement:

- 1. Long-Term Temporal Dependency:** The LSTM model has demonstrated a difficulty in accurately predicting long-term dependencies. To improve the accuracy of long-term predictions, more advanced LSTM designs may be implemented, such as the LSTM - Attention model.
- 2. Generalization to Out-of-Distribution Data:** The capacity of the LSTM to generalize out-of-discipline data must be improved in order to effectively manage unknown events and network configurations. To address this issue, methods such as domain adaptation or transfer learning may be explored.
- 3. Data Imbalance:** The dataset had some class imbalance, with a higher number of non-congested instances compared to congested instances. Employing techniques such as oversampling, undersampling, or using class weights during training could help mitigate this imbalance.
- 4. Model Explainability:** While we employed visualization techniques for model interpretability, further research into advanced explainable AI methods could lead to better insights into the models' decision-making processes.
- 5. Real-Time Implementation:** Deploying the prediction system in real-time network monitoring requires optimization for low-latency performance and considerations for handling data streams.

Addressing these limitations and exploring potential improvements could lead to even more robust and accurate Prediction of Network Congestion for queuing of call drop in mobile communication, empowering network operators to proactively manage network performance and enhance user experiences.

## 1.9 Operational Definition of Terms

- **Call Drop:** A call drop is a phenomenon in which the signal from a mobile device is lost, resulting in the inability to make or receive incoming calls.
- **Queuing in Mobile Communication:** Queuing theory is a mathematical approach to the study of queues. The purpose of a queue model is to predict the length of queues and the length of the waiting period.
- **Mobile Communication:** This is the utilization of technology that enables us to interact with others in remote locations without the need for a physical connection (e.g. wires or cables).
- **Network Congestion:** Network congestion is a decrease in the quality of service due to a node or connection sending more data than the network is able to cope with. Common reasons for congestion include queued delays, packet losses, and blocked new connections. When congestion occurs, an incremental increment in available load will either result in a slight increase or decrease in network throughput.
- **Quality of Service:** This is more focused on traffic prioritization and resource booking than service quality, which is the ability to provide different priorities to different applications, users, or data flows, or to guarantee a certain level of performance across a data flow.
- **Mobile Stations:** This is the term used to refer to a device that is connected to a worldwide mobile network, typically a mobile telephone or a mobile computer via a mobile broadband adapter.
- **Base Stations:** It is defined as the primary mode of communication for one or more mobile client devices that utilise this type of fixed transceiver.

- **Machine Learning Algorithms:** These are the methods that Artificial Intelligence systems use to accomplish its objective, which typically involves anticipating the outcomes from the input data.

## Endnotes

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## Chapter Two

### Literature Review

#### 2.1 Introduction

Wireless communication has a wide range of applications that significantly enhance consumer welfare, thus its importance and value cannot be overstated. This is due to the features, amenities, adaptability, and mobility it provides. The mathematical analysis of queuing in mobile communications is known as queuing. By constructing a model of queuing, it is possible to forecast the number of queued lines and the length of the wait times. Queuing systems are responsible for the efficient allocation of resources within telecommunications networks and remain a highly sought-after subject of research. Different modulation algorithms are already being used, which makes the user reliant on the base station's signal strength. Queueing, also known as queues, is a frequent occurrence in our lives. The main characteristic of a queuing is a group of physical individuals (people or objects) queuing or queueing according to a set of rules of conduct before certain services are rendered one by one or for each individual in the queue<sup>1</sup>. Queueing is a common occurrence wherever there is a high level of competition for limited resources. To effectively manage incoming calls and manage call transfers more efficiently in the context of the increasing demand for wireless communications networks, a promise of service (QoS) must be implemented<sup>2</sup>. As the demand for wireless communications systems continues to grow, the promise of QoS must be met in a satisfactory way in order to effectively manage incoming new calls as well as handover calls. Handover calls are a critical factor in wireless and cellular communications systems due to the mobile nature of devices, and thus have a direct impact on service quality<sup>3</sup>. This is the mechanism by which an ongoing call is transferred from one mobile device to another as the user progresses through the cellular system's coverage area. As cellular systems are limited in

capacity, it is essential to utilize handover calls in the most effective manner. Different CAC models have been analyzed in the past to identify performance issues<sup>4, 5, 6</sup>.

## 2.2 Retrial Queues

The retrial queue has been the subject of research for a variety of computer and communications networks, including wireless cellular networks. This particular kind of queueing mechanism is responsible for retry, which is the practice of retrying incoming requests that are found to be "full" or "occupied" in a cell after a set period of time, in either a random order or in a first in-first out (FIFO) order<sup>7, 8, 9, 10, 11</sup>. Retrial queue models can be applied to a variety of real-world scenarios, such as retail shopping, where a customer who encounters a lengthy queue may opt to do something else in order to return to the store later with the expectation that the queue will have dispersed. In reality, the notion that customers who abandon the system due to a lack of channel resources are lost is only a first approximation of the reality. Usually such a customer returns to the system after a random time interval and tries to get service<sup>12, 13</sup>. Retrial queues have been shown to improve customer satisfaction and network quality<sup>14, 15, 16, 17</sup>. Requests are either denied or suspended, thus consuming network resources. As a result, requests cannot be met. The retrial queue is designed to reduce such wastage by allowing requests that are at risk of being denied access to the resource stream to retry the request without exiting the network. The retries could be performed for an indefinite period of time or randomly. The study has only considered the initial retries. Subsequent retries may result in the withdrawal of the request if it is not serviced, as more retries will, if allowed, lead to an increase in network congestion, as the same limited network resources are reused to process new requests<sup>18</sup>.

### 2.2.1 Standard Retrial Queue Models

Requests are rejected or blocked, resulting in a waste of valuable network resources. Consequently, these standards cannot be met<sup>19, 20</sup>. A retrial queue allows requests that are at risk of being denied access back into the resource stream without leaving the network to reduce such waste. Retrials may occur on a regular basis or for an indefinite period of time. The study only looked at the first round of retries, following which the request may be withdrawn if it is not fulfilled. If retries are permitted, network congestion will increase as, after the initial retry, new requests are processed using the same limited resources<sup>21, 22</sup>.

The Retrial queue model has been used in a range of research paradigms, as well as an alternative priority method for the handover call (i.e. an additional queue). The Handover Retrial Method and a Guard Channel Design were discussed<sup>23</sup>. Recursive Analysis was employed to assess the intricate cell structure of the system. The Analytical Model developed using the Recursive Method was used to assess the system performance metrics. Two models addresses the Call Retry Problem in a Mobile Communication System<sup>23</sup>. The first model focuses on Base Stations with a limited client base and Retrievers. The second model focuses on the application of the guard channel concept to the prioritization of handover requests, the implementation of the recursive methods and the application of the Markov chain to the calculation of the state probability<sup>24, 25</sup>. The impact of client retries was then considered while evaluating the network's QoS. To evaluate the network's QoS in relation to client retries, a novel approach was developed in the form of known as Modelling, Specification and Evaluation Language (MOSEL). MOSEL was used to study the cellular network's functionality and to roughly address the issue of retry queues<sup>26</sup>. Models were developed and system performance indicators were calculated using MOSEL. In addition, a rough methodology was used to assess the performance of an asynchronous retrial queue (M/M/2) in which both servers experienced both active and inactive failures. Algorithmic and

approximate approaches have been demonstrated to be effective in resolving complex analytical problems<sup>27</sup>.

The desired QoS measurements for an isolated cell subjected to multivariate CAC within a mobile wireless network, a primitive approach and a cutoff approach have been employed<sup>28</sup>. A mathematical approach for constructing simple approximative Continuous-Time Markov chain (CMTC) models, with state spaces that expand linearly with the concurrent call count within a cell, has been proposed<sup>29</sup>. This method has been employed to evaluate the probability of a call being blocked by considering customer retrials that are the result of a blocked new call or a failed handover. However, retrial queue analysis is a challenging and often inflexible process, and the computational strategy and approximation analytical technique are both used in the literature<sup>30, 31, 32</sup>. Neither approach has been found to provide the required level of precision and numerical consistency for such systems.

### **2.2.2 Integrated Computational and Analytical Approach**

This method was developed to facilitate the creation and analysis of real world systems, while also minimizing system analysis complexity. The analytical methodology was based on a 2D Markov process and a Phase-Merging technique, while the computational methodology was based on the matlab /simulink block-orientated simulation environment. The 2D CTMC is an effective and efficient tool for the description and study of a random process characterized by state transitions. For retrial queueing schemes, it is challenging to derive steady-state probabilities due to the transition between or within layers of the 2D CTMC. To accurately describe the system, model complexity must be examined. Establishing the best design criteria is critical in order to enhance network service standards and minimize system complexity. The following performance metrics are required to be considered: Blocking Probability with Retrial (PBR), Blocking Probability without Retrial (PBT), Handover Call Drop Probability (PH), Retrial Queue Length (K), Retrial Rate ( $\alpha$ ), etc.

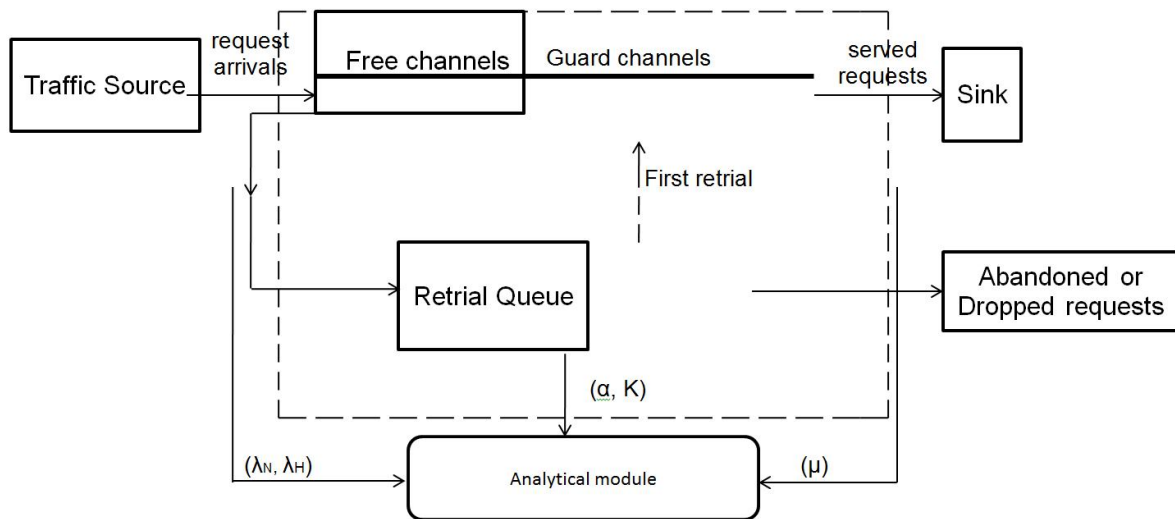


Figure 2.1 A Comprehensive Model of the Retrial Queue for Wireless Cellular Networks<sup>35</sup>

### 2.3 Handover Calls

The growth of cellular communication has stimulated a surge in cellular system research and development. The primary driver of this growth is the concept of a mobile terminal, and the notion that mobile communication systems enable maximum freedom of movement through the use of mobile phones.

Handover is a method of switching a mobile station's network connection access point (MS) without erasing data or interrupting existing connections. To ensure a successful handover, two base stations must be reached simultaneously, both from the handover destination and the current base station, however, this is not always necessary. The transmission of a call between a mobile device in one cellular area and a mobile device in another is referred to as handover. Handover is a critical component of a cellular mobile network, as it guarantees that a call will continue to be received. Efficient handover approaches are required because radio resources are used for handovers and changeover processes have an effect on system interference, user satisfaction, and capacity. As the system's handover rate increases, there's an increased chance of a call being dropped because there's no free channel. In a non-priority scheme<sup>36</sup>, a new stalling call and a handover failure are the same thing. To increase the

likelihood of new call blocking and reduce the likelihood of handover dropping handover priority techniques, reduce the total permitted traffic. The principle behind the above handover priority techniques is to reserve a small number of channels called guard channels for handovers<sup>37</sup>.

There are two reasons for performing a handover:

- **Handover as a Result of Measurement:** happens when a specific Base Station controller (BSC)-specified metric is not fulfilled for the radio signal's quality or intensity. The continuous signal measurements made by both connection and handed off to a cell with a stronger signal allow for the detection of the signal deterioration.
- **Handover Due to Traffic Reasons:** occurs when a cell's bandwidth has reached or is about to reach its maximum. The mobile stations on the cell's boundaries can be subsequently transferred to cells nearby with reduced traffic loads in this case.
- Except for traffic-related handovers, the BSC that currently provides service to the subscriber makes the decision to make a handover call. In the latter case, the Mobile Station Controller (MSC) makes the decision. However, from a user's perspective, dropping an ongoing call is not as desirable as blocking a new call attempted. Fractional guard channels (FGC) scheme which allocates a non-inclusive number of guard channels to handover calls by receiving new calls with a certain probability that depends on current channel occupancy<sup>38</sup>.

However, from the point of view of the user, dropping an on-going call is not as desirable as blocking a call attempt. FGC, on the other hand, allows a non-consistent number of guard channels to be used for handover calls, accepting new calls with a probability that depends on current channel occupancy<sup>39</sup>.

Cellular systems distribute smaller cells to meet the demands of higher system capacity due to the limited spectrum available. Each handover requires the network management to redirect the call to a new base station, thus increasing the number of expected handovers. Mobile devices remain within the range of a single base station (BS) throughout communication. The received signal strength (RSS) of Mobile stations is determined by the distance between the Mobile station and the base station. When the received signal strength drops below a threshold, the handover process commences. The decision to handover is based on the received signal strengths of current and neighbouring base stations. The Mobile Station (MS) that is relaying signals from a Base Station to a different Base Station is illustrated in Figure 2.2. The signal is expected to be averaged over time, thus eliminating any rapid fluctuations caused by the multipath of the radio environment. The average signal strength of the Mobile Station decreases as it moves away from the Base Station, and the average signal strength increases as it approaches the Base Station. The Mobile Station is able to measure the signal strengths of the surrounding Base Stations, as well as the interference levels of all channels. Handovers can be initiated when the signal strength of one or more serving base stations is below a certain threshold. If the received signal strength of the current base stations does not exceed the receiver threshold level before the mobile is assigned a channel to the target cell, the call is dropped. As the frequency of handovers increases, the drop probability also increases. Various handover methods have been proposed and applied in various cellular networks<sup>40, 41</sup>.

### **2.3.1 Handover Calls: Types**

In cellular network systems, there are two distinct types of handovers:

- a. Hard handover
- b. Soft handover

### 2.3. 1.1 Hard Handover

The implementation of hard handover involves the release of a communication channel first and the subsequent acquisition of a new channel from the adjacent cell for real-time users. This results in a brief interruption of communication, resulting in a decrease in service quality. This is the method employed by systems that utilize TDMA (Time Division Multiple Access) and FDMA (Frequency Division Multiple Access) including GSM and GPRS.

These are some of the main causes for establishing various types of handover. They are as follows:

- **Intra- Cell Base Transceiver Station:** In the context of frequency change, transfer of a transceiver station is commonly referred to as intra-cell transfer or intra-base transfer. Although the two terms are often used interchangeably, they differ slightly. The concept of intra-cell transfer differs from intra-base transfer in that the frequency of a call is shifted when the quality of the communication link is decreasing and the measurement of adjacent cells is more precise than that of the current cell.
- **Intra – BS Controller:** Intra-Base Station Controller Handover (IBC) refers to the transmission of the MSC to the Base Transceiver Station (BTS) but not to the Base Station Computer (BSC). The MSC is informed of the intra-Base Station (BSC) turnover, but the transfer is solely controlled by the BSC. If the target cell is in a different region, the MSC must carry out the location update procedure after the call. Interim handover is possible either asynchronously or asynchronously.
- **Intra- Mobile Switching Station Handover:** When the BSC determines that an intra-MSC handover is necessary, but the cell is in the custody of another BSC, it requires the action of the MSC associated with it. The cell is then assigned to different BSCs that are connected by the same MSC. During the intra-MSSC

handover, the MSC contacts the BSC in question to request the allocation of resources and informs the BSC when the process is completed. Upon successful resource allocation, the call is relocated to the new BSC, prompting the MSC to connect to the new channel.

- **Inter- Mobile Switching Center Handover calls:** The inter-MSC handover occurs when two cells from different MSCs exist simultaneously in the system. The target cell is connected to an MSC other than the one currently transmitting the call MSC.

## 2.4 Handover Performance Evaluations

The following elements are used as numerical representations of the handover performance. :

- **Number of Handovers:** This number quantifies the number of handovers that occurred during the mobile terminal's transition between a series of parallel Base Stations.
- **Ping-Pong Handovers:** The Ping-Pong handovers consist of multiple overlapping Base Station coverage bands, which consume radio and network signaling power without being required.
- **Number of Handover Attempts:** This is the maximum number of times a mobile device and a new base station have tried to make contact before a stable connection is established.
- **Blocking Probability (Pb):** The cause of the refusal is the lack of available channels. Consequently, the refusal of the request leads to the blocking and its likelihood, known as blocking probability.
- **Handover Probability (Ph):** A successful handover refers to a mobile's connection being successfully transferred from one base station to another base station. The term

"handover probability" is used to refer to the likelihood that a mobile's connection will be successfully transferred from a base station to a different base station.

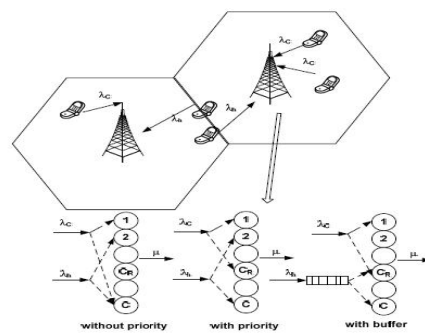
- **Dropping Probability (Pd):** If no successful handover can be accomplished in the route, the network will be forced to terminate the call. The term "dropping probability" is used to denote the probability that the call will be terminated.

In order to evaluate network performance, it is necessary to take into account the overall sequence of daily activities, as well as to evaluate congestion conditions. Performance metrics include traffic, call setup success rate, handover success rate, stand-alone dedicated control channel blocking rate, and transport channel blocking rate. The traffic is chosen in such a way that it can be used to quantify the increase in service and channel demand. It is an estimate of the resulting congestion. Call setup and handover success rates are selected to gain insight into the impact of congestion on subscribers' service levels during the two most critical call attempt operations. Due to the fact that the relevant channels are the most affected in a congested environment, the Standalone Dedicated Control Channel (SDCC) and Traffic Channel (TCH). Blocking Rates are selected in order to identify where exactly congestion occurs from the perspective of logical channel. These two channels are the primary resources that the system relies on to satisfy the user's requirements. The likelihood of traffic blocking is a key parameter used to assess handover performance. If the user is forced to terminate a handover call, it is preferable to prevent a new call. There are three different channel assignment schemes to consider when assessing this parameter: no priority, with priority and with buffer.

The analysis of a network comprises two distinct types of traffic:

- Cell

Traffic



- Handover traffic

Fig 2.2 Channel Assignment Scheme<sup>42</sup>

The probability of traffic being blocked was examined in the context of Markov chain analysis. Each state in Markov chain is represented by the number of channels occupied<sup>43</sup>,<sup>44</sup>. All traffic is assumed to follow the Poisson arrival with an average velocity of  $\lambda_C / \lambda_H$ . They exhibit an exponential time-to-service ratio with an average rate of  $1/\mu$ . In the case of a priority-less channel assignment scheme, the steady-state probabilities are calculated as in<sup>45, 46</sup>.

$$P(j) = \frac{(\lambda_C + \lambda_H)^j}{j! \mu^j} \cdot p(0), \text{ if } 0 < j \leq C \quad 2.1$$

$$P(0) = \left[ 1 + \sum_{j=1}^C \left( \frac{\lambda_C + \lambda_H}{\mu} \right)^j \cdot \frac{1}{j!} \right]^{-1} \quad 2.2$$

where  $\lambda_C$ ,  $\lambda_H$  is the arrived intensity of cell and handover traffic,  $\mu$  is the traffic service intensity. Then the blocking probabilities of the cell and the handover traffic are given by:

$$P_{b_c} = P_{b_H} = P(C) \quad 2.3$$

In the case, when priority scheme of the channel assignment is used, the steady- state probabilities are calculated by:

$$P(j) = \frac{(\lambda_C + \lambda_H)^j}{j! \mu^j} \cdot p(0), \text{ If } 0 < j \leq C_{CH} \quad 2.4$$

$$\frac{(\lambda_C + \lambda_H)^C \cdot \lambda_H^{j-C}}{j! \mu^j} \cdot p(0) \quad 2.4$$

where

$$p(0) = \left[ \sum_{j=0}^c \left( \frac{(\lambda C + \lambda H)^j}{j! \mu^j} \right) + \sum_{j=cc+1}^c \frac{(\lambda C + \lambda H)^{cc} \cdot \lambda H j - cc}{j! \mu^j} \right]^{-1} \quad 2.5$$

The expression for the calculation of the blocking probability of the cell traffic is

$$Pb_c = \sum_{j=cc}^c P(j) \quad 2.6$$

The blocking probability of handover traffic can calculate using equation:

$$Pb_H = P(c) = \frac{(\lambda C + \lambda H)^{cc} \cdot \lambda H j - cc}{C! \mu^j} \cdot P(0) \quad 2.7$$

When the buffer scheme of channel assignment is used, the steady – state probabilities are found as follows:

$$P(j) = \begin{cases} \left( \frac{\lambda C}{\mu} \right)^j \cdot \frac{1}{j!} \cdot P(0), & \text{if } 0 \leq j \leq C_c \\ \frac{(\lambda C)^{cc} \cdot \lambda H j - cc}{j - c} \cdot P(0) & \text{if } C_c \leq j \leq C, \\ \frac{(\lambda C)^{cc} \cdot \lambda H j - cc}{j - c} \cdot P(0) & \\ C! \mu^c \prod_{i=1}^c (c + i \mu_1) & \\ i = 1 & \end{cases} \quad 2.8$$

where

$$P(0) = \left[ 1 + \sum \left( \frac{\lambda C}{\mu} \right)^j \cdot \frac{1}{j!} + \sum_{i=cc+1}^c \frac{(\lambda C)^{cc} \cdot \lambda H j - cc}{j! \mu^j} + \sum_{j=c+1}^{c+Q} \frac{(\lambda C)^{cc} \cdot \lambda H j - cc}{j - c} \right]^{-1} \quad 2.9$$

The expression of the blocking probability of cell traffic calculation is:

$$P_{b_c} = \sum_{j=cc}^{c+Q} P(j) \quad 46 \quad 2.10$$

The blocking probability of handover traffic can be calculated using following equation:

$$P_{b_H} = \sum_{j=cc}^{c+Q} P(j) \cdot P(T > T_p) \quad 46 \quad 2.11$$

The results of the calculation demonstrate that, for handover, channel assignment schemes with buffers are preferable. Conversely, for cell traffic, channel assignment with buffers is preferable when the handover traffic concentration is low. On the other hand, when handover concentrations are high, it is probable that the cell traffic congestion will be lower for non-priority channel assignment schemes as compared to buffer channel assignment schemes. The 3GPP examined a range of technologies with the aim of expanding cellular network capacity, including MM-Wave Communication (MM-Waves), HetNets (Heterogeneous Networks), Multiple inputs, Multiple outputs (MIMOs), 4G Advanced (4G Advanced and Beyond), and more. The emergence of heterogeneous networks, composed of multiple small cells with varying capacities, has been widely accepted as a key technology to provide services to a wide range of users, alongside other technologies. Examples of such heterogeneous networks include RHA (Remote Radio Head) and PICO eNB. Low power micro cells offer enhanced user coverage while decreasing the load on macro cells. Adoption of heterogeneous networks could, however, lead to further disruption of mobility. Two alternative approaches to address this issue are Coordinated Multipoint and Dual Connection. In these clusters, the electronic network nodes (eNBs) communicate with each other and process signals together. Furthermore, a number of Unified Environments (UEs) can process their signals independently or in combination, while simultaneously receiving them from one or multiple transmission points. To minimize signaling overheads and feedback delays, we provide a dynamic coordinator-based CoMP control architecture. Additionally, they investigate CoMP techniques, implementation architectures, and the advantages and disadvantages of each. As

mentioned earlier, Dual connection allows Unified Environments to establish simultaneous control and data plane connections with two or more electronic network nodes.

The performance of a non-prioritised and reserved channel allocation strategy in a WiMAX network. The results of the study measured the failure rate for handover, forced terminal, incomplete, and blocked calls was conducted<sup>47</sup>. To improve radio spectrum utilisation, the network was equipped with cognitive radio technologies. Based on the simulation results, the performance attributes of CRBCS (Cognitive Radio Based Channel Scheme) demonstrated some average values. The guard channels served as a buffer, with incoming and outbound handover calls being queued and a guard channel being added to the guard channel pool when new calls became available. Additionally, a control admission call was used to allocate adaptive bandwidth for the wireless mobile system network. The proposed strategy significantly reduced the number of handovers and intermediate call times compared to the no-prioritized bandwidth-adaptive approach, while also blocking more new calls than rejecting them.

#### **2.4.1 Soft – Handover**

Soft handover refers to the process of creating multiple connections with neighboring cells, as opposed to the hard handover method. This is a common practice in the multiple access system of the CDMA Code Division, where cells have the same frequency band, but different code words are employed. Every Member State has an active set of cells, which are added BS when a remote signature service provider surpasses a threshold, and removed BS when the threshold drops below a predetermined threshold for a specified period. The active set of cells is subject to soft handover regardless of whether or not a BS is present. Examples of soft handover schemes are:

- Handover of Macro Diversity (MDHO)
- Fast Base Station Switching (FBSS)

#### **2.4.1.1 Handover of Macro Diversity (MDHO)**

A set of BSs taking part in the handover process is contained in the diversity set. The MS and BS are responsible for maintaining the diversity set, and MAC (Medium Access Control) management messages are used to update it.

Each mobile station in the network is associated with a diversity set. The MS chooses one of the Anchor Base Stations (AB Stations) as one of the base Stations included in the Macro Diversity Handover packages. The MS has an interaction with the diversity set provided by the AB Station, the active base Stations and user traffic.

#### **2.4.1.2 Fast Base Station Switching (FBSS)**

A diversity set is maintained to guarantee a smooth transition between mobile stations using this method. Neighboring BSSs that may be included in this diversity set are kept at the forefront of the serving BSS as well as the MS. To initiate the switchover, the MS selects one base station from the diversity set to act as the anchor. The MS receives information regarding the BSSs current position and forwards this to the BSS Controller, who is then able to make a handover decision. For each necessary handover, the BSS Controller notifies the MS through handover integration transmissions, depending on the implementation. There are two main types of network congestion:

- New Call Congestion.
- Horizontal Handover Congestion

Congestion management strategies have been compared and analyzed to determine which ones may be applicable to the current situation. Horizontal handover congestion, for example, is mainly caused by handover communications, while new call congestion, on the other hand, is primarily caused by incoming calls. The following congestion management schemes have been taken into consideration: Call Admission Control, Auxiliary Station, Guard Channel,

Handover Queuing Priorities Schemes, and Priority Schemes. The following systems have taken steps to mitigate the risk of congestion-induced handover failure rate when they were identified<sup>51</sup>. The terms "call admission control," "guard channel prioritization," and "handover queue prioritization" were used to describe the three schemes. Additionally, they referred to a methodology known as the Load-Balancing and Cell-Overlapping scheme, which could be used to achieve efficient handovers in areas of congestion. The preventive and reactive control techniques were employed to manage congested areas<sup>52, 53</sup>, and that reactive control could be used to manage congestion while using feedback data to reduce its severity. They further noted that network monitoring tools could be used to provide raw data as well as graphical representation of network status, allowing for the tracking of what is happening and the identification of areas where adjustments are necessary. The tools could also help to address important issues such as accurate estimation and performance parameters<sup>54</sup>.

The congestion can be alleviated by utilizing Network Resource Allocation (NRAs) and Call Admission Control (CACs). Network Resource Allocation would determine the rate at which incoming connection requests are accepted, while Call Admission Control would adjust the rate at which new calls are accepted or rejected based on the available network resources<sup>55</sup>. Network resources and minimize congestion, guard channels and buffers should be combined with enhanced QoS standards for incoming and outgoing calls as well as dedicated guard channels<sup>55</sup>. Network congestion management based on traffic class prioritizing was evaluated. Each type of traffic would be classified into one of several classes on the GSM network, each with a distinct level of priority. Higher priority classes would receive service prior to lower priority classes<sup>56</sup>. The algorithm was simulated and the simulation's performance was evaluated using OPNET Modeller 17.5, a simulation software. A mathematical model that would be based on a priority queueing system, however, call

admission management has been extensively discussed in the literature as a method of congestion reduction<sup>57</sup>. The survey was also used to collect qualitative data regarding service performance metrics (e.g., signal strength, call dropping probability, etc.), clarifying the need for call admission control in order to collect these metrics<sup>58, 59</sup>. The design criteria that were used to classify the call admission control approach were: centralisation; information scope; service dimension; optimisation; decision time; data type; granularity of data; and considered links; and the two different call admission control systems (centralized and distributed) were grouped under the centralised design criterion. The call admission control system categories<sup>60</sup> is defined, according to their information scale design criteria, which include global, semiautonomous, and local systems for call admission control. They also acknowledged single service class, multi-service class, and proactive and reactive system call admission control types according to their decision time design criteria. Furthermore, according to their information type design criteria, these systems were classified as cell occupancy, mobility, and single cell-based<sup>61</sup>. Finally, according to their considered link requirement, the systems were classified as user-based.

## 2.5 Vertical Handover

In heterogeneous wireless networks, handover is known technically as a vertical handover.

There are two categories of handover algorithms based on the handover criteria:

- **The Standard Handover Algorithms:** They take into account parameters such as signal strength, distance, speed, power consumption, etc.

- **Intelligent Handover Algorithms:**

Algorithms for handover are based on artificial intelligence (AI) techniques, including pattern recognition, fuzzy logic, neural networks and prediction<sup>62</sup>. The criteria for making handover

decisions and the techniques for processing them can be divided into different categories. To illustrate the differences between handover algorithms we compared them, we firstly looked at the Mobile Velocity - Distance algorithm, the Cost Function Algorithm, and finally the Receiving Signal Strength Algorithm<sup>63, 64</sup>.

#### **i) Receiving Signal Strength based Vertical Handover Algorithms**

The vertical handover algorithm based on RSS is the primary factor to consider when making a handover decision. It is essential to compare the strength of the receiving signal of the current point of connection to another point of connection in order to make an informed decision<sup>65, 66, 67</sup>. The following is an overview of the vertical handover algorithms that are based on RSS.

#### **ii. Bandwidth based Vertical Handover Algorithm**

The realization of a high system is made possible with the help of this method. For delay-sensitive applications, throughput and lowers handover delay. The main vertical handover decision-making criteria is considered to be available bandwidth<sup>69, 70</sup>.

#### **iii. Cost Function based Vertical Handover Algorithms**

These algorithms combine parameters like bandwidth, financial cost, power consumption, and security into a cost function, and then compare the results of this function for the candidate networks to determine which network should take over during a handover<sup>72, 73</sup>.

The vertical handover of heterogeneous network selections aims to select the network that is most appropriate for the user. However, this can result in partial networks having an excessive number of users connected to the network, leading to congestion and a decline in customer service<sup>74</sup>. To address this issue, the optimization algorithm is used to create a network allocation matrix which meets user requirements. This approach, as described in the Network Load-Balancing approach transforms the problem of network-balancing into a problem of optimization<sup>75</sup>. In order to achieve a balanced network utilization, the

optimization algorithm is employed to identify the most optimal allocation strategy. This optimization technique is also employed to balance several networks in order to meet the QoS requirements of various services<sup>76</sup>. The modelling results demonstrate the effectiveness of the algorithm proposed for implementation in public wireless network. To improve the overall performance of the network, a comparison method was evaluated. This comparison method compares two variables: cell boundary crossings (crossing the cell boundaries) and handover execution (handover execution)<sup>77</sup>. The signal strength assessment serves as the primary criterion for determining whether or not to transfer to the target cell. A fuzzy logic model to enhance the handover method in heterogeneous networks<sup>78</sup>. Two modifications of the Transmission Weighting Parameter (TWP) in the Heterogeneous Network handover<sup>79</sup>. The first modified algorithm employs entropy to evaluate the transmission metric, whereas the second modified algorithm employs standard deviations weighting to evaluate the relevance of a transmission metric. Both modified algorithms are employed to rank items based on their similarity to technique for order priority by similarity to ideal solution Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). Base stations are viewed as transmission control options in a heterogeneous network. Simulation findings shows that the proposed solutions are more efficient than current methods by reducing transmission frequency and radio failures and increasing average user throughput compared to traditional methods<sup>80</sup>. Performance management (PM) data is now extracted from network constituents and transmitted to NMS, the business intelligence tool focused on monitoring and monitoring network performance. Performance management data contain named counters and other metrics needed to measure network performance. In addition to the fundamental limitations on the amount, type, and velocity of performance management data collected, scaling is also a common feature of modern NMS systems. The big data framework on the basis of an analysis of software design elements, data transit elements, processing elements, reporting

elements, and deployment elements in a real dataset derived from four different data sources<sup>81</sup>. The results of the component test as well as the reports are presented. Telecommunication firms can use these guidelines to set up a comprehensive data reference system to manage current and future calls on their new cellular networks. A novel concept for a fog-based computing system to facilitate device communication for improved QoS and QoE. The recommended task is the one with the least latency, power usage, and signaling cost. The potential benefits and major challenges associated with the implementation of 5G and its objectives, as well as the drawbacks, future deployment plans, and current progress in standardization<sup>83</sup>. Machine learning can be utilised to optimise and enhance the functioning of 5G networks. As user traffic is rapidly increasing and mobile networks are undergoing changes in their nature and architecture, it has become apparent that the capacities of these systems need to be continually and significantly increased, as they have already reached the channel bandwidth limits<sup>84</sup>. This necessitates the improvement of radio resource assignment management techniques and the spatial compactification of radio interface technologies. In order to enhance network performance, the utilization of heterogeneous networks containing cells of different sizes is recommended<sup>85</sup>. This is due to the numerous technological challenges associated with network design, avoidance of inter-system disruption, the organization of transport networks, the management of networks and their own organization, the control of mobility, and other similar issues. Additionally, the strategic objectives of cloud technologies and Software-Defined Network Functions Virtualization (SDN / NFV) are also taken into account, as SDN/NFV seeks to capitalize on a range of potential client risks, resulting in increased network efficiency and service flexibility<sup>86, 87, 88</sup>.

The results of the study demonstrate that the current approaches to optimizing mobile networks are not equipped with the necessary technology to manage heterogeneous networks in a flexible, scalable, flexible, cost-effective, and user-friendly manner<sup>89</sup>. To address this

issue, an algorithm was proposed based on a light correspondence framework to account for a variety of features, including dynamic network parameters, as well as actual traffic preference, despite a decrease in handover. This method utilizes measures for technical progress and a useful simulation model. The handover issues were given less attention due to the presence of numerous target networks during vertical handover, however, the algorithm necessitated that the network transmission rate be taken into account<sup>90</sup>. An handover algorithm was optimized with the combined fuzzy logic theory and the multidimensional decision making which was used to select the optimal network<sup>91</sup>. However, this algorithm did not utilize the Network Attribute Signal-To-Interference-Plus-Noise Ratio<sup>92</sup>. The handover calls necessitated additional efforts. In addition to RSS, additional input parameters should be included to overcome the shortcomings of the current horizontal handover algorithm. RSS-based judgments are not suitable for two-tiered networks and present a high level of running complexity<sup>93, 94</sup>. New challenges arise due to the high density of heterogeneous electronic network nodes (eNBs) in a restricted coverage area as well as the fact that the eNB has a higher transmitting power compared to the HeNB (sufficient for greater coverage)<sup>95</sup>. The HeNB has a lower transmitting power. Based on these findings, a novel method, Mobile Velocity - Distance (MVD) was developed which periodically surveys the distance between UE positions while taking into account UE velocities and directions<sup>96</sup>.

## **2.6 Horizontal Handover Algorithm**

Horizontal handover method based on adaptive hysteresis was proposed for the GSM network<sup>97</sup>. The hysteresis value can be predicted using a model that takes into account two factors: the distance between the mobile station and the serving base station and the coverage radius of the base station. The handover process begins when the RSS of any nearby base station surpasses the RSS of a serving base station. The separation distance is used to adjust the handover margin, while the RSS is primarily taken into consideration. The methodology

was found to be more effective than the traditional handover strategy, however, it did not take into account the traffic at the nearby base station during the base station transition, which could lead to call drops and handover delays<sup>98</sup>. Additionally, the paper outlines a method for automatically disconnecting handover margin optimization for GSM and GPRS networks. The variability of the handover margin, which is not adjusted for actual traffic, is based on the difference in the likelihood of a base station being blocked relative to its surrounding BS. A positive outcome of the analysis is that the call loss rate is reduced and traffic handling is improved despite a decrease in call quality. To improve call quality, one of the key performance criteria should be included in the optimization process. To manage congestion in heterogeneous networks, load balancing was employed as well as an adaptive hysteresis margin<sup>99</sup>. A mobile network's significant challenges in terms of load balancing and Hysteresis margins was employed<sup>99</sup>. To modify the handover technique, the author employed quality indicators in signal to noise ratio (SNR). The load balancing decision for mobile networks was based on the CIO (Cell Individual Offset) value and traffic loads on both serving base stations and new base stations. The outcome of the research revealed that the schemes were effective in improving the success rate of handovers and operated efficiently, however, the methods necessitated a considerable amount of mathematics. It was proposed to employ a soft computing methodology that combined fuzzy logic and neural networks for mobile device load balancing for communication, which was first introduced<sup>100</sup>. On the basis of three derived parameters (Virtual Load of the serving Business Systems, Number of Disaffected Users in the Serving Business Systems, and General Load Condition of the Target Business Systems), an Adaptive Handover Hysteresis Margin was calculated with Artificial Intelligence. Although some calculations were not required, the simulation results appear to have been successful<sup>101</sup>. It is suggested that the number of Disaffected Users on the entire Network should be replaced by a performance metric, such as SNR, or even Base Station

throughput and the handover choice for the cellular mobile system was made by integrating Load Sharing, Direct Retry, and Neural Networks and a Congestion Control Method based on a Traffic Class Priority Algorithm was developed in<sup>102, 103, 104</sup>. The method prioritised the real network traffic based on its importance. It was determined that a combination of Priority Queuing (PQ), Weighted Fair Queuing (WCFQ) whereas WCFQ should be implemented. The performance of each class was assessed by examining the traffic served. Traffic was efficiently categorised according to the algorithms, with the higher priority given to that traffic. The priority algorithm ensures that the lower priority traffic is dropped instead of the less important traffic, thus avoiding any impact on congestion control performance. To improve congestion control performance it is recommended to implement a hybrid system combining the proven algorithm with a load balancing handover mechanism<sup>105</sup>. It is also suggested to implement a distributed load balancing system for mobile communication networks, which would involve the implementation of a separate handover control for balancing the load. The algorithm simply took into account the available channel within a base station. On the basis of quantum and temporal statistics, a round queuing method was used for calls waiting for channel assignment.

The call blocking rate was used as a benchmark for performance evaluation. It was found to be significantly more efficient than a standard system without load balancing. This approach was adopted regardless of any quality of service requirements, such as RSS, SNR and others. In order to balance load, a fuzzy logic multi-paraquet handover mechanism was implemented<sup>106</sup>. The handover decision was generated by a fuzzy inference system, which took into account the RSS, traffic load, SNR, and path loss of the base station, resulting in a handover decision based on the values of the four input parameters. However, this method could not be used to assess the suitability of target base stations, as the requesting Mobile Station did not possess the SNR or PL measurements that the algorithm required. These

parameters could only be measured by the Member State using the serving Base Station's Bandwidth. Contrary to our advice, the fuzzy controller should not take into account these two parameters. A fuzzy logic multi-parahedron handover method based on the RSS data, the traffic load, the SNR data and the Path Loss data of the supplying BS balanced load was developed<sup>106</sup>. The fuzzy inference system produces a handover decision by taking into account the values of these four input parameters. However, this method is not suitable for assessing the suitability of target base stations, as the requesting MS does not possess access to the measurements of SNR and PL required by the algorithm. Only the MS from the supplying base station is able to measure these metrics. Therefore, it is recommended to remove these two parameters from the fuzzy controller input.

## **2.7 Device to Device-Aware Handover Solution**

This approach minimizes the amount of signaling overhead required to reduce delay. As illustrated in Figure 2.3(a), when two devices are stable, there is a typical level of communication between them. However, when UE1 switches between two stations that are served by different base stations, there is a large amount of overhead that needs to be avoided. This is not possible due to the additional waiting time. To significantly reduce latency, an algorithm for a group handover should be implemented. The condition where the RSRP target- RSRP source > offset is considered an A3 occurrence should be addressed. The intention was for one base station to control both devices; however, they offered to postpone the handover process for each device until this requirement is met. The specific steps required to accomplish this activity are outlined in the Figure

2.3(b).

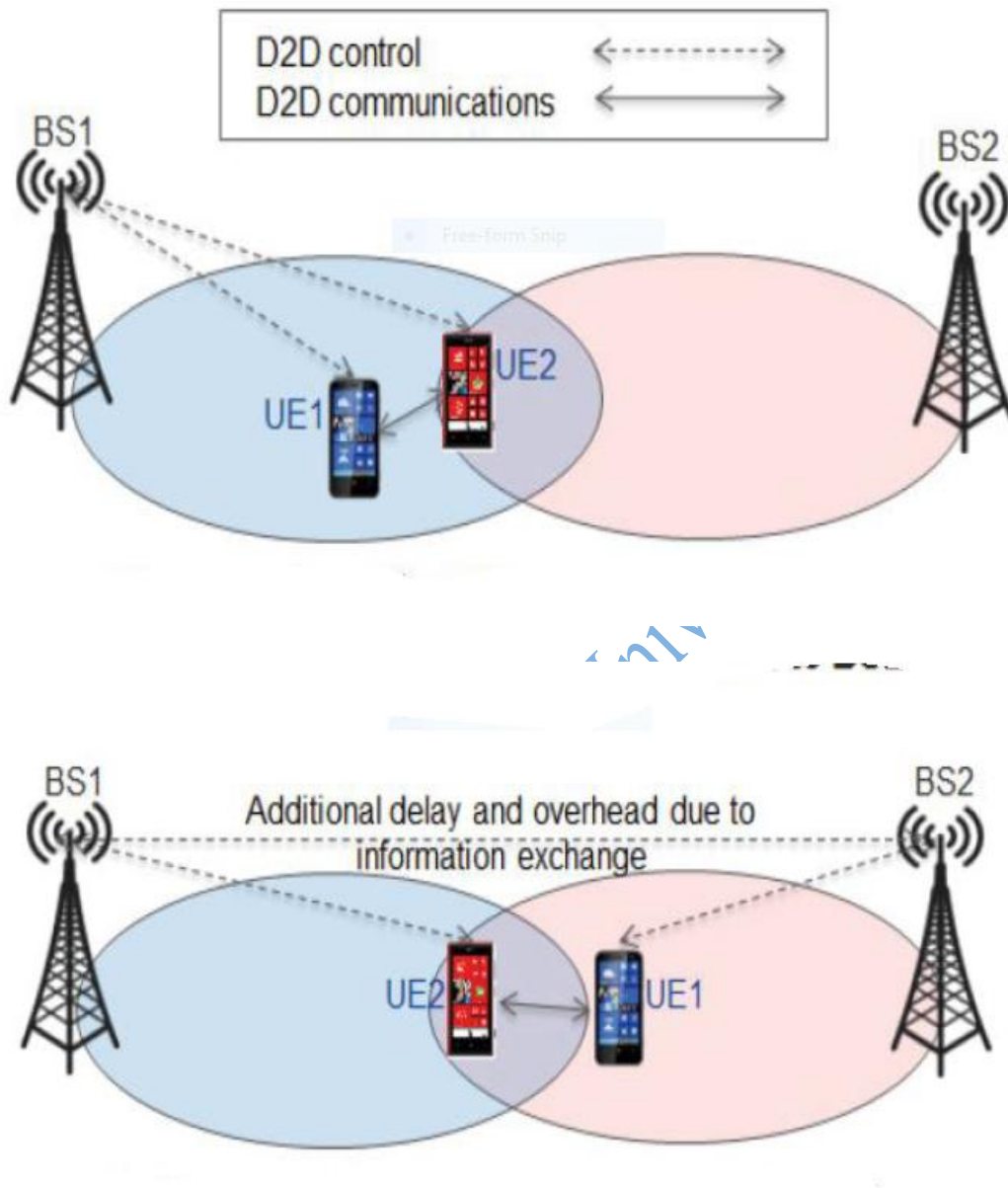


Fig. 2.3 (a) and (b) A Standard Cellular Handover Execution for two-way Communication and Control (D2D)<sup>110</sup>

### 2.8 Device to Device-Triggered Handover Solution (D2D)

Figures 2.3 (a) and 2.3 (b) illustrate a signalling flow chart illustrating a handover procedure initiated by D2D, in which a target cell coordinates the transfer of a new user to a group communication. The purpose of this type of solution is to minimize the network signalling

overhead generated by inter- BS, such as the communication of radio resource information between D2D groups by aggregating all members of the group into a limited number of BS or cells<sup>111</sup>.

## 2.9 Handover Management

This method facilitates the transfer of a mobile device from one network attachment point to another while maintaining a continuous transmission. Additionally, network access control is included in the handover process when a new network attachment point necessitates roaming into a different network with a different provider.

The handover procedure can be broken down into three distinct phases.

1. **Handover Initiation:** At this stage, the necessary evidence is collected to evaluate the need for a handover. It is possible to provide information on the network, the network-related components, the mobile device, the access point, and the user's preferences.
2. **Handover Decision:** This stage determines the time and point at which to execute the handover by choosing the relevant access network (based on predetermined parameters) and guiding the execution phase.
3. **Handover Execution:** The execution phase is the part of the handover process where the actual handover takes place. During this stage, the channels in confirm are updated to reflect the data resolved during the decision phase.

Once the information necessary for the handover has been collected, network binding updates initiate during the execution

phase.

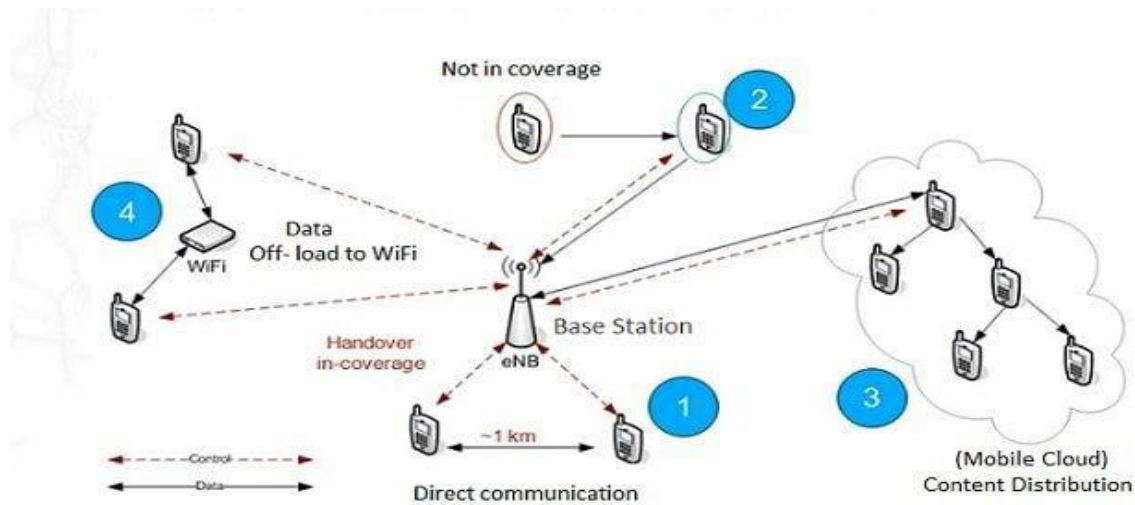


Fig. 2.4 D2D in 5G Communication Network<sup>112</sup>.

Depending on the conditions, there are a variety of methods of achieving D2D communication. To ensure efficient transmission, the optimal operating mode will be determined based on the available devices.

**Scenario 1:** When two devices come into contact with each other, they can communicate with each other, such as sharing data. This enhances the data rate, decreases the device power consumption, and reduces the overall load on the base station. The base station will then control the communication.

**Scenario 2:** When the cellular network is idle or signal reception is inadequate, devices that support D2D enable the creation of a 5G communication interface between a node and its surroundings, which are connected mobile base stations. This allows a node that lacks cellular coverage to stay connected to the mobile network.

**Scenario 3:** It is possible for a single device to connect to a device that is connected to an active base station and to extend the network by connecting to other devices. All devices in this mini mobile cloud receive the same data in the form of advertising or communication from the source.

**Scenario 4:** In this example, multiple devices are interconnected via the Wi-Fi network for communication. The base station is responsible for sending control signals to these devices. Offloading via Wi-Fi provides substantially higher data rates, lower power consumption and avoids base station congestion.

## **2.10 The Advantages of D2D Communication**

Network efficiency offers a range of benefits which includes reduced power consumption and extended battery life, efficient traffic load management, the capacity to establish connections even when no Network is present, the ability to extend the network without the use of complex hardware, D2D communications, public safety and security services, vehicle to vehicle communication, autonomous driving applications, cellular offloading to wireless local area networks for faster data transfer, gaming and local social networking, content distribution, local advertising, location-aware services, and local area emergency broadcast.

## **2.11 Classification of D2D Communication**

There are two distinct forms of device-to-device communication: In-band communication and Out-band communication. The primary distinction between the two modes of communication is the frequency range in which the communication is transmitted.

### **2.11.1. In-Band D2D Communication**

**D2D Cellular Users in the 5G:** The network infrastructure is responsible for controlling the use of licensed cellular spectrum for in-band communication. This includes the identification of potential devices, the allocation of radio resources based on channel status, the control of power based on predetermined threshold levels, and the coordination of interference between mobile and device users.

In-band D2D communication can be divided into two distinct categories:

- Underlay
- Overlay

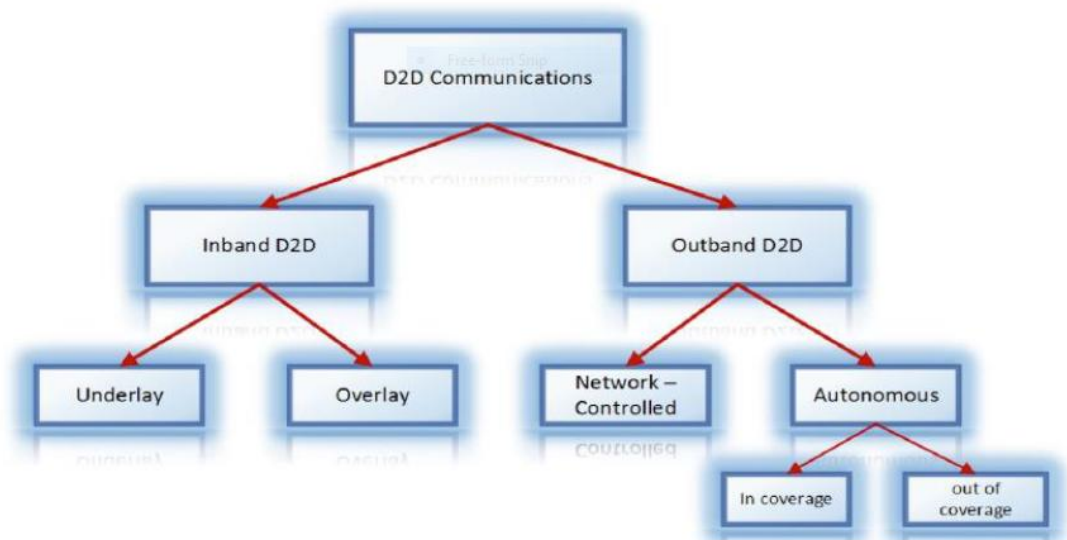


Fig. 2.5 The Classification of Digital Two-Way Communication (D2D)<sup>113</sup>

### 1) Underlay In-Band

**Underlay In-Band:** The eNB simultaneously allocates the same radio spectrum as it does to device to device users reuse mode. The Embedded Network Bridge (eNB) leverages the device's uplink (or downstream) resource blocks for communication between the eNB and the cellular users based on a range of performance parameters, including the distance from the device to the cellular users, transmit power level, interference limitation area, etc. Another name for this type of implementation is Non-orthogonal Resource Sharing, which is depicted in figure 2.6.

The reuse mode has a higher spectrum efficiency than overlay.

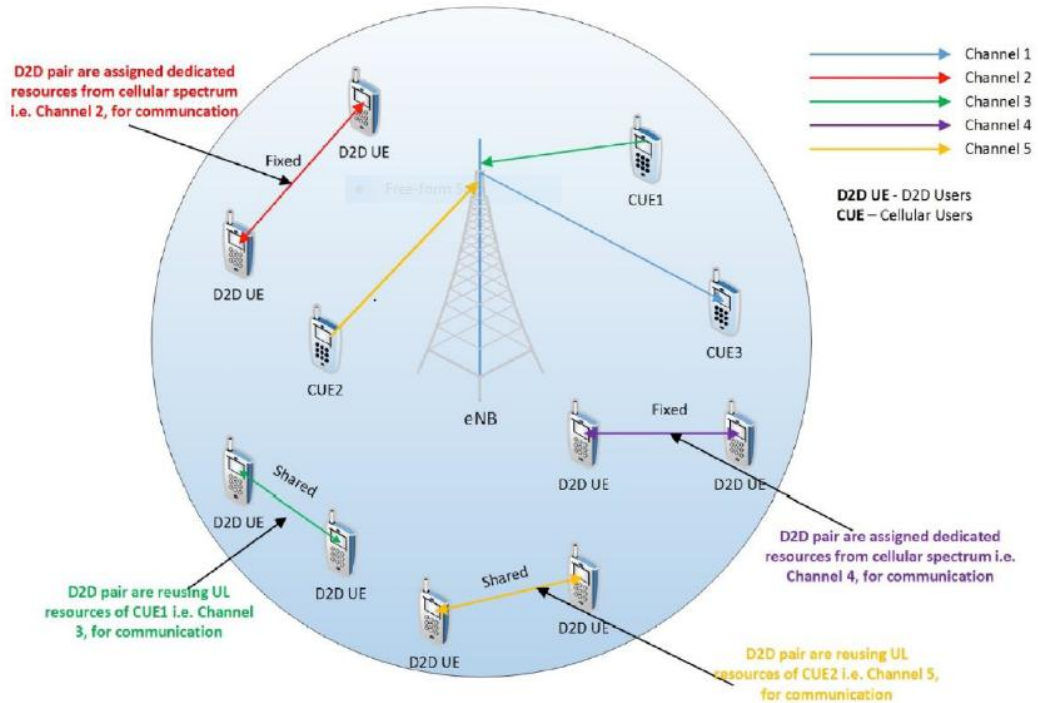


Fig. 2.6 A Cell made up of D2D using Different Modes of Communication<sup>114</sup>.

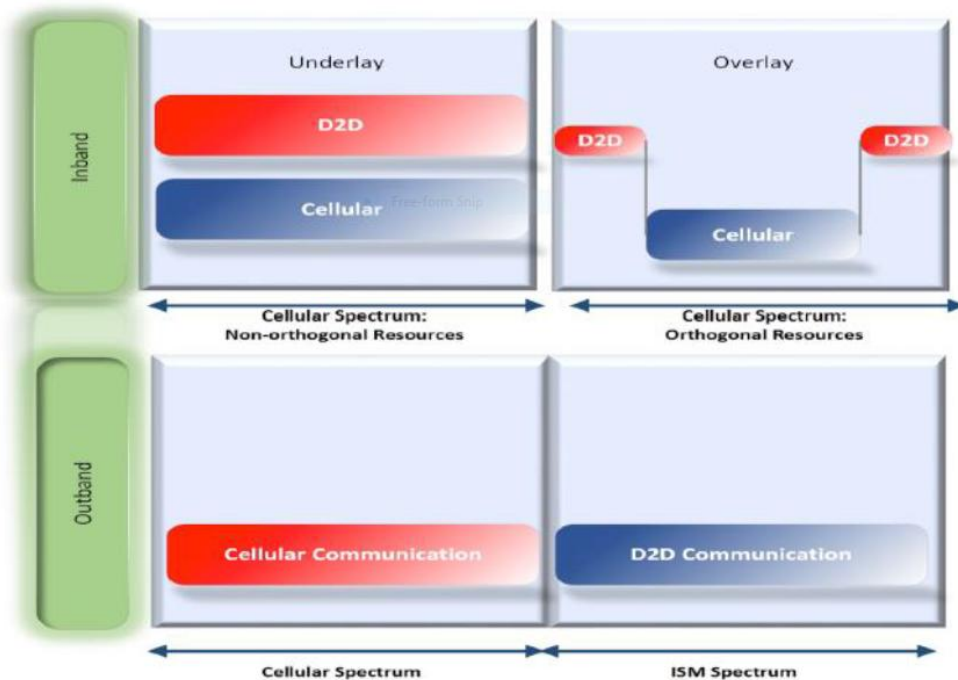
However, since both users are using the same physical resources at the same time, this leads to a significant interference problem between device-to-device and device-to-cell phone users. Since mobile users make up the majority of the users in the spectrum band, enabling device to mobile communication on this frequency band means that the level of service for mobile communication and the level of reliability for both communications needs to be addressed. There is a lot of literature on this topic that focuses on finding innovative solutions to all the problems mentioned above.

## 2) Overlay In-Band

The electronic network band (eNB) facilitates fixed orthogonal communication between devices in D2D mode (also known as Dedicated Mode) by providing fixed bandwidth from

mobile band. As each communication mode occupies a particular block of physical space, there is no longer interference between mobile and devices in DM. However, as a number of D2D links are able to utilise the same RBI for their transmissions, some degree of cellular to device-user interference between DM users is still present, resulting in a reduction in network capacity. In comparison to DM, the in-band overlay has the major disadvantage of not utilizing radio resources optimally. This is because the allocated resources are left in optimal condition while no DM session is present, resulting in an inefficient spectrum utilization. The spectral efficiency of underlay devices to devices is higher than that of overlay devices, which has led to their increasing adoption in industry and academia alike. For example, in the single cell scenario illustrated in Figure 2.7 below, the cellular users are distributed randomly and the D2D user is distributed randomly. Some of the device to device pairs reuse the CU's (Centralized Unit's), Uplinks resources for D2D communication, while other couples utilize non-obligatory

Uplinks



resources.

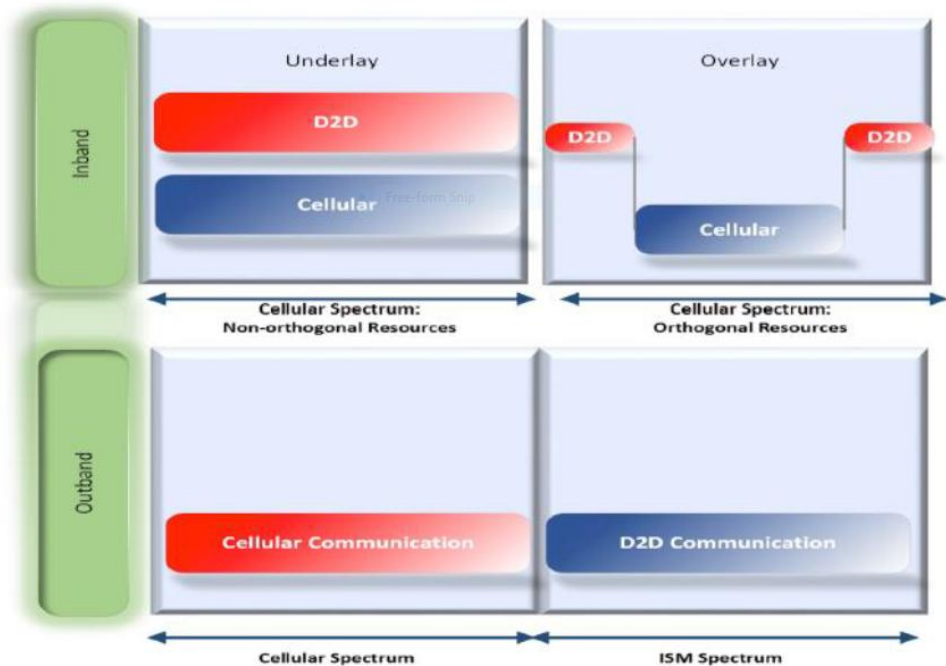
Fig. 2.7a Frequency Band Occupancy of D2D in Cellular Networks<sup>116</sup>

### **2.11.2 Out-Band D2D Communication**

The Unlicensed ISM Frequency Spectrum is utilized for the operation of Out-of-Band Device to Device Communication which is analogous to the Wireless Local Area Network (WLAN) and Bluetooth Operational Band (BHB) <sup>117</sup>. In Outband Device to Device Communication, the End-to-End Network (eNB), also known as Network-Controlled, or the Device to Device User (D2DU), also known as Autonomous, is able to coordinate and manage the connection between devices. The primary advantage of this form of Device to Device Communication is that it addresses the issue of Interference between cellular and Device to Device networks. The Scheduler (eNB) is free to allocate resource blocks to both Device to Device (D2D) and Cell User (C2C) users, the allocation of resources becomes more straightforward. The use of these two radio interfaces allows users to maintain cellular and device-to-device connections at the same time. However, as other communication entities operate in the unlicensed band (Wi-Fi and Bluetooth), the primary disadvantage of sharing unlicensed spectrum is its uncontrolled inter-system interference, which could lead to congestion, a suboptimal Quality of Service (QoS) experience, and a decrease in overall network throughput.

### **2.11.3 Device to Device-Triggered Handover Operation**

The signaling flow chart presented in Figure 2.7b illustrates a handover operation from a device to a group communication. In this method, a target cell is responsible for the transfer of a new D2D user to the group communication. By aggregating all members of a D2D group into a few Base Station (BS) or Cell, this approach sought to minimize the network signaling overhead associated with inter-base station communications, such as the exchange of D2D



information.

Fig 2.7b Signaling flow chart of a Device to Device-triggered Handover Process<sup>116</sup>

## 2.12 Global System for Mobile Communication

The Global System is a second-generation, digital cellular network composed of cells, which are the fundamental components of the global mobile communication infrastructure. This region, which is equipped with base station transmitters, is referred to as a cellular (BST) area. In order to provide services to the greatest extent possible in a given location, the cells are utilized to serve the greatest number of customers in a given area. The Global System utilizes three frequency spectra to maximize the frequency channels available to it. These spectra are always mixed, with FDMA and TDMA being the most common. The NCC's quarterly audit of global system network performances reveals that operators often fail to meet their stated standards due to congestion in the network<sup>117</sup>. As hardware issues and interference are not taken into account, the congestion is usually due to access of network elements<sup>118</sup> that do not have enough radio channel capacity to transmit data. Cellular communication networks are divided into smaller areas known as cells, each of which contains a MSS and a few Mobile

Hosts<sup>119</sup>. While cable links are typically used to communicate between MSs, wireless links are used to connect MHs and MSs. A MS can communicate with other MSSs through the MSS in its cell only. When this occurs, it is referred to as a BS Handover Congestion. An example of a Mobile Communications Network Handover is shown in the accompanying

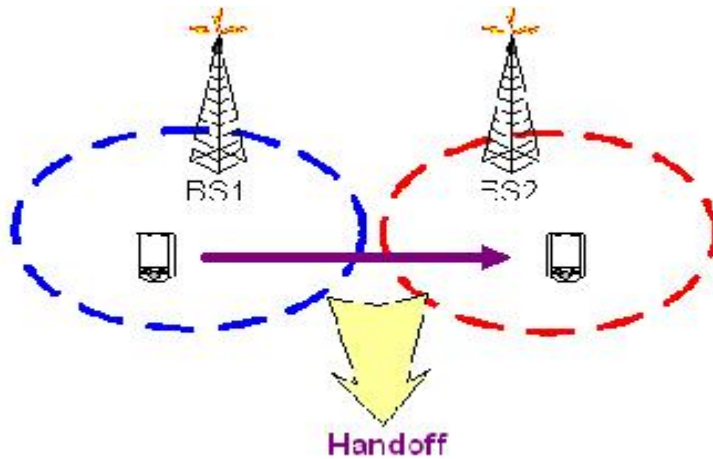


image.

Fig 2.8 Handover of a Mobile Telecommunication Network<sup>120</sup>

Early studies have demonstrated that the performance of the GSM network components is largely dependent on the access area of the network, particularly at the Bandwidth Transmitting System (BTS) level. For example, a traffic model based on the Markov chain to calculate the probability of call blocking and call handover failures when there is no call queueing for a new or handover call was evaluated<sup>121</sup>. The traffic data was collected in the office to simulate the effect of user mobility on mobile network performance<sup>122</sup>. Location updates were also evaluated to determine the probability of a call drop when a handover call is required. Seventy eight traffic channels were analyzed to demonstrate that a single dedicated GSM/ GPRS channel is sufficient for good quality of service<sup>123</sup>. GSM/Reservation of more channels brings handover failure and dropped call probability to very small values but lack of ordinary channels produces a larger new calls blocking probability<sup>124</sup>.

The performance metrics used were Traffic, Call Setup Success Rate, Handover Success Rate, Standby Dedicated Control Channel, and Traffic Channel Congestion. The analysis revealed that the system was not able to cope with the exceptionally high demand without additional resources<sup>125</sup>. A model was constructed which included simulations for Page Signaling and Traffic channels in order to assess the appropriate dimensions of a single physical resource distributed across multiple logical channels with different traffic types. Daily measurement data was used in the study to assess the performance of two different vendors' GSM1900 um-interfaces over a week<sup>126</sup>. The performance indicators used are: peak hour traffic (CSSR), Handover Failure (CSSR + Handover Failure), Congestion on Control Channels (SDCCh Blocking Rate), Congestion On Traffic Channels (TCH Blocking Rate), Drop On Traffic Channels, Drop On Control Channels, Cells with TCH Congestion Rate Exceeding 2% and TCH Average Holding Time and the traffic data from an Ecomm Trunked Radio Network in the UK using the OPNET Model<sup>128</sup>. The results indicated that typical Voice Traffic Erlang models may not be suitable for evaluating the performance of trunked Radio Networks<sup>130</sup>. A Dynamic Channel Allocation Model using the Markov Chain Technique was developed<sup>129</sup>. This model was used to reduce Handover Failure and make it easier to adhere to Quality of Service (QoS) standards for continuous conversations. However, the disadvantage of this solution was that new calls were being prohibited more frequently as fewer conventional channels were available. The solution should have an improved resources for maintaining the Network's QoS<sup>13, 132</sup>.

## **2.13 Call Stages**

### **1. Call Blocking**

When initiating a call on a mobile device, if all channels of communication are congested, mobile will attempt to resume the call. After a series of unsuccessful attempts, a "Busy Tone" will be returned.

## 2. Call termination

The user has concluded the call, and the Mobile Telephone Switching office (MTSO) has been notified. Additionally, the traffic channels at two BS points have been released.

## 3. Call drop

The Base Station was unable to maintain the desired signal strength, resulting in the loss of the Traffic Channel and the notification of the MTSO.

## 4. Call to/from and Remote Mobile Subscribers

Mobile Telephone Switching offices (MTSOs) are equipped with the capability to connect to Public switched telephone networks (PSTN), allowing for the connection of mobile users and fixed subscribers. Additionally, MTSOs can be connected to remote MTSOs via the PSTN or through dedicated lines. Furthermore, MTSOs are able to connect mobile users in their area and remote mobile users.

**5. Mobile Station (MS):** This concept is analogous to the mobile phones.

## 6. Base Station (BS)

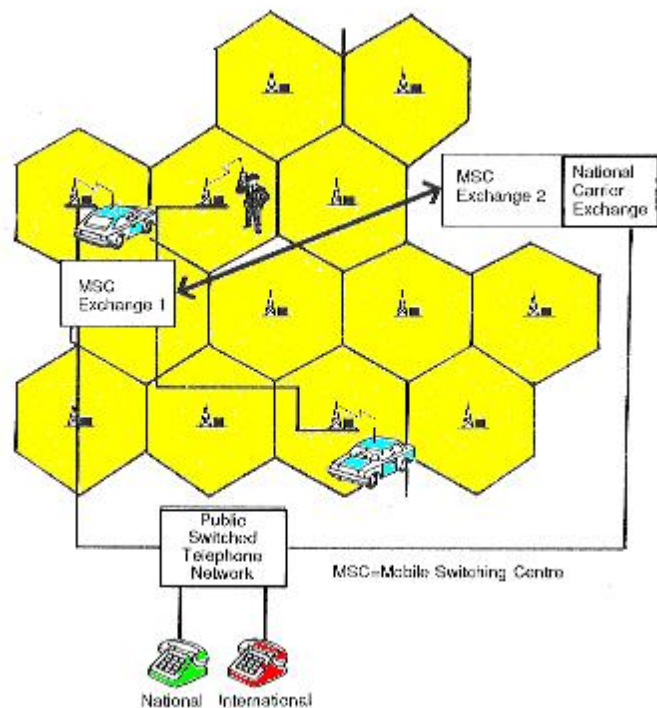
The cellular network is divided into distinct areas referred to as cells, by which the covered area is divided into smaller areas. Each cell is connected to a BS which simultaneously communicates with all of its mobile devices and transmits traffic to a mobile switching center. The mobile phone is connected to the base station via a radio interface.



Fig 2.9 Base Station<sup>133</sup>

6. **Mobile Switching Centre (MSC):** This encompasses the management of multiple cells (or clusters), the organization of base stations and mobile channels, and the management of connections.

7. **National Carrier Exchange:** This is the access point to the National Fixed Public switched Telephone (PSTN). It manages interconnections on behalf of the National Communication Systems and is typically interconnected with the Multi-State Communication System



(MSC).

Fig 2.10 Public Switched Telephone Network (PSTN) <sup>134</sup>.

### 2.14 Channel Allocation

Two basic approaches to channel allocation are as follows:

1. **Centralized approach:** This is the interface to the PSTN, which is responsible for interconnecting National Communication Systems, and is usually connected to the MSC.

2. **Distributed approach:** Distributed channel allocation algorithms do not involve the involvement of a central controller such as an MSC. Rather, the allocation of channels is a

shared responsibility of the MSSs. Each MSS makes its own decisions based on its local data. To ensure that the set of available channels is determined in such a way that the use of them does not result in any co-channel interference, MSSs share information when necessary. Generally, one of the two primary approaches—either the on demand/reactive approach or the proactive approach—is employed when implementing a distributed channel acquisition methodology.

**a. On Demand/Reactive Approach:** When a cell requires access to a channel to facilitate a call, the first step is to determine if any of the available channels are assigned to the cell. If available, the cell will select one of the available channels to facilitate the call. In other cases, the cell will communicate with adjacent interference sources to obtain information on their channel usage. The cell will then compute the set of available channels using the information from the responses.

**b. Proactive Approach:** When a cell obtains or grants access to a channel, it informs its interfering neighbors of the associated channel usage data. Consequently, each cell is aware of the available channels. To support a communication, the cell simply selects one of the channels using the channel selection mechanism, after verifying that none of its neighboring cells are using it. Most on demand / reactive algorithms require that a cell wishing to borrow a channel, referred to as the borrower, must first obtain a response from each interfering neighbor before utilizing a channel.

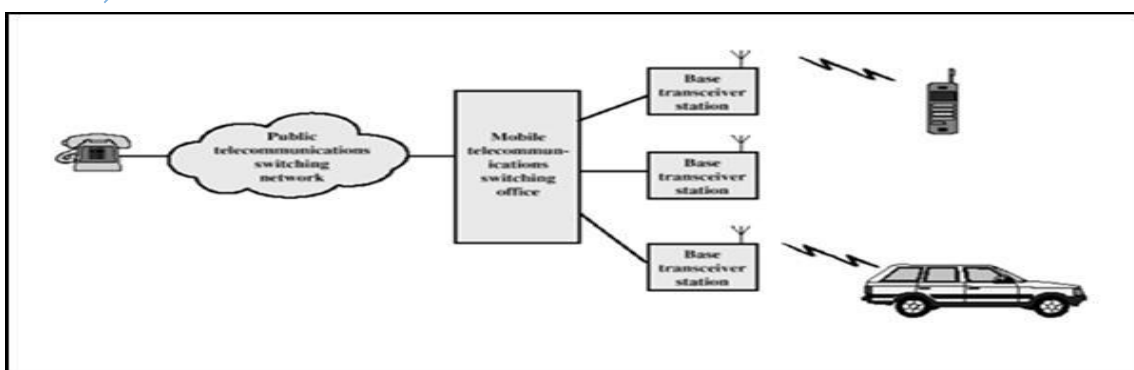


Fig 2.11 Underlying Channel Selection Strategy<sup>135</sup>

This approach implies that, even if a branch of the neighbouring cell has failed, the channel cannot be loaned out, thus not being fault tolerant. One of the primary benefits is the proposed algorithm for the allocation of channels that is distributed and fault tolerant and that reuses channels effectively<sup>136</sup>.

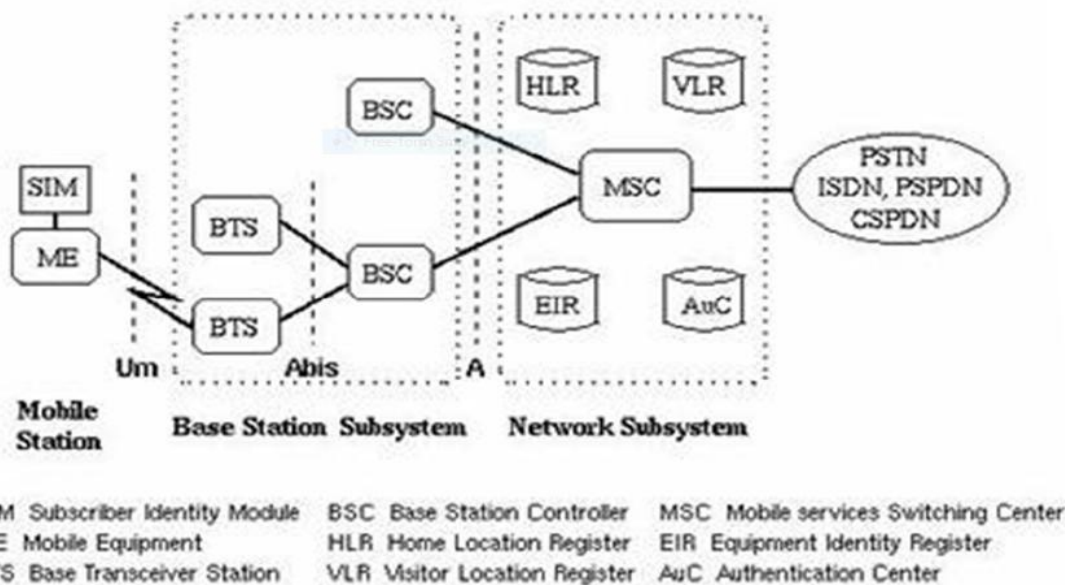


Fig 2.12 Fault-tolerant Channel Allocation<sup>137</sup>

## 2.15 Utilization of the Spectrum in Cellular Networks

### 1. Frequency Re-use

The number of concurrent calls that can be made in any radio network is largely determined by the frequency spectrum available and the available bandwidth for channels. In a traditional radio system, groups or areas are assigned specific radio frequencies. To guarantee that these channels remain free from interference from other users, adequate separation between transmitters should be taken into account when allocating frequencies. In a cellular network, frequency reuse<sup>138</sup> is accomplished by assigning a portion of the total channels available to

individual base stations and regulating the transmitters' power output. This increases the capacity of the network, as adjacent cells cannot operate on the same frequency as the base stations, as this would cause interference between them. It is evident from the foregoing statement that the multiplication of cells within the covered area, i.e., the reduction in cell size, would lead to an increase in capacity. However, this approach raises a number of issues.

**2. Interference:** Reducing the number of cells, particularly when the repeat factor is low, increases the likelihood of interference between cells utilizing the same frequency.

**3. Handovers:** Reducing the size of the cell will lead to an increase in the number of handovers, as a mobile device that is constantly on the move will be exchanging cells more frequently. As the MSC requires a certain amount of time to make the switch (in the case of handovers), an increase in the handovers will result in an increase in that time delay.

## **2.16 Microcellular Systems**

Microcellular systems are composed of a number of cells, each with a zone site and a base station of its own<sup>139</sup>. It is essential to remember that each microcell within a cell utilises the same frequency, and if there is no transfer of information regarding the mobile unit's location and a method of providing limited power to the unit, the channel capacity will be increased without any problems between the microcells. The signal used to find the mobile unit in the cell zone selector of the base station is utilized to select the zone with the highest signal strength as the zone suitable for the operation of the mobile unit.

### **2.16.1 Base Station Signals**

When a call is received, the system is already cognizant of the mobile device's location. The base station, on the other hand, is aware of the area in which mobile devices are located. As soon as it receives the signal, the base station transmits it to the designated zone site. The zone site then amplifies the cellular signal, reducing the amount of co-channel interference

between zones and increasing system capacity by reducing the amount of power transmitted to the device.

### **2.16.2 The Benefits of Microcellular Systems**

**1. Interference** minimized (as opposed to reducing the cell size).

**2. Handovers:** The size of the cell is reduced due to the microcells operating at the same frequency within the cell; there is no transfer of data between the mobile unit and the microcells.

**3. Size of the Zone Apparatus:** Zone site equipment are typically of a small size, allowing them to be installed on the sides of a building on poles.

**4. Increased System Capacity.** The microcell is a smart cell that recognizes the location of the mobile unit within a specific area of the cell and transfers the power to that area. As the signal power is decreased, the microcells are able to be closer to the mobile unit, resulting in an increase in capacity. Microcellular systems necessitate the accurate transmission of power to mobile phones within the microcell system, which can be detrimental if the power is too strong or weak, as it can disrupt the communication between other microcells. If the power is not sufficient, the signal cannot be received by the phone. This is a drawback of microcell systems, as it requires the transmission power to be adjusted as the environment changes, for example, when a new building is constructed within the microcell.

### **2.17 Multiple Access Systems**

Multiple access systems are utilized in digital cellular networks to enable multiple users to access the same channel within the same cell. Two of the most popular methods of multiple access are Time Division Multiple Access (Time Division Multiple Access) and Frequency Division Multiple Access (FDMA). In Time Division Multiple Access, the bandwidth allocated to the channel is split into time slots, with the number of slots varying depending on

the system used. Each user is assigned a slot, thus multiple users are able to share the same frequency at different times. Frequency Division Multiple Access, on the other hand, divides the channel into frequency bands and assigns each user a frequency band.

### **2.18 Handover Process**

Following the installation of network equipment, there are usually some unexpected issues that arise. The process by which a user can move between cell areas while maintaining the availability of the network begins to become evident. This process is referred to as the "handover process". As a customer progresses through the cell area of a cellular wireless network, a handover process occurs in which an active call is transferred or transferred from one area to another. To handle a handover, the new base station system must be chosen that has a free channel for accepting new handover calls, and the handover call must be cancelled<sup>140, 141</sup>. The MSC may, instead of terminating the call to the current MS, transfer or transfer the call to another easily accessible and more efficient base station system or, in some cases, to a different mobile switching center.

The following figure 2.13 illustrates the Call to/From and Remote mobile subscriber handover

process.

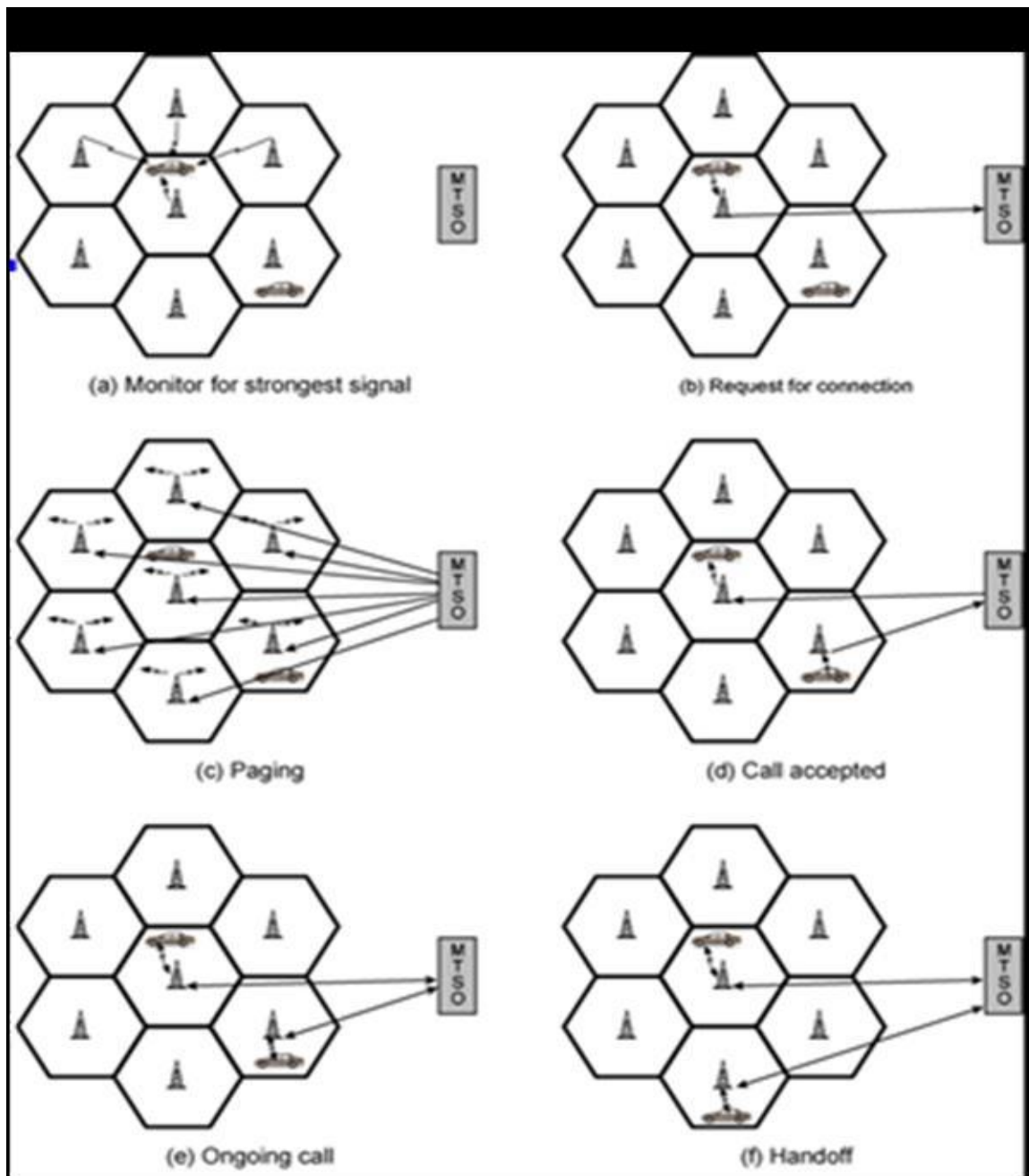


Fig 2.13 Call to/from and Remote Mobile Subscriber<sup>142</sup>

GSM technology offers a higher rate of call retention, thus improving Quality of Service. The handover process is therefore of paramount importance, as a malfunctioning handover process could result in call drops. An effective communications infrastructure is essential for the growth and development of any economy, and is essential for daily activities and in times

of national emergencies or natural disasters. Additionally, it reduces the risk and inconvenience associated with travel. As the majority of economies lack reliable communication networks, it is beneficial for any nation to have access to efficient telecommunications infrastructure, which is one of the most interesting features of the modern telecommunications sector. The emergence of new generations of cellular networks has enabled the provision of a wide range of services, including voice, data and video. Mobile networks with the latest level of connectivity (5G) offer voice, number calls and data connections to the client. The use of mobile devices is becoming increasingly essential in our lives, as they enable us to carry out everyday tasks and foster technological progress. This has resulted in an increase in the number of mobile users, which in turn has caused a decrease in bandwidth. In recent times, a range of data links have been physically connected via mobile devices, leading to a hand-over process. As a result, operators must now increase their network's capacity to provide effective services to meet the increasing demand. Wireless networks must adhere to service quality requirements in order to operate more effectively. QoS, decreased power requirements, consistent mobile coverage, and other factors are just a few of the considerations that users make when selecting a mobile operator. When customers, also known as consumers looking for services, enter a facility and are unable to be quickly supplied, a queue is formed. A mobile network is composed of interconnected nodes that are able to connect to each other without the need for a fixed network infrastructure. Each node in a mobile network can act as a router, sending packet to other nodes. This allows the router to make decisions that can lead to unexpected and dynamic changes in the network topologies, as the node can also serve as an end point for the user. This fundamental issue of mobile network performance must be addressed by service providers and telecom regulators in order to meet the needs of their subscribers. The assessment of congestion on the network is based on key performance indicators, such as busy hour traffic pattern. Network congestion has a

detrimental effect on the network's quality of service (QoS), particularly during peak hours<sup>143</sup>. KPIs (Key Performance Indicators) are defined for a variety of GSM / GPRS network interface and network components. RF optimization teams use these indicators to generate QoS reports to ensure that there is minimal congestion across all interface and network elements thus preventing QoS degradation by maintaining the KPIs below predetermined thresholds<sup>144, 145, 146</sup>. These indicators are employed to create multiple KPIs, which are then used to evaluate network performance using different formulations. In real-world applications, network performance may be monitored at various nodes. In this work, network performance is evaluated at the cell level, taking into account resource allocation and consumption. Previous studies on GSM network components were mainly focused on the access area of the network, particularly at BTS level. Service providers must continually monitor and optimize their network in order to achieve optimal performance and meet regulatory target metrics for Key Performance Indicators (KPI). Traffic data used to model the effect of user mobility on mobile networks and the mobile network traffic model is based on Markov chain, which quantifies the call blocking probability and handover failure probability when no queuing or handover calls are made<sup>147, 148</sup>. Location updates were also evaluated to assess the probability of a call dropping in the event of a handover. The seventy eight traffic channels were examined, and a single dedicated channel was found to be sufficient for acceptable Quality of Service (QoS)<sup>149</sup>. A set of dedicated GPRS channels were also used, with some quiet intervals between voice calls, to test the GSM / GPRS system's performance. Reservations of more channels reduced the handover failure and drop call probability to very low values, but the lack of ordinary channels resulted in a larger new call blocking probability<sup>150</sup>. The three primary criteria for evaluating the quality of service (QoS) of an operator in a telecommunications (voice) context are accessibility, retention and connectivity. In this example, the hosts, switches and routers are the nodes, whereas the links are the actual

physical connections between the nodes. As long as the nodes have linkages, information can be exchanged between them as data packets.

## **2.19 Call Drop in Cellular Networks**

Call drop is a technical issue that occurs when a conversation breaks off before the two parties have finished their conversations, leading to one of them having to hang up. Connected calls may also be disconnected due to a technical issue, without prior permission from the participating parties, leaving them in a hung up state. To address modern cellular network problems, most research has focused on the issue of call drop in mobile networks<sup>151</sup>. This research has focused on abstract representations of the network, in which only Call Admission Control, QoS, Call Block and Drop solutions are taken into account. This paper was inspired by the development of mathematical approaches to solve the problem of call admission control. The paper was developed using Markov decision processes, fuzzy logic and neural networks, as well as genetic algorithms, and was trained through a certain learning process to automatically maintain a preemption rate between previously allocated resources and a new call request<sup>152, 153</sup>.

### **2.19.1 Concept of Self Learning for Reducing Call Drop Rate**

#### **a. Load Balancing and Sharing**

When a serving cell's network signal strength surpasses the threshold value, it must be compared to the signal strength of its neighborhood cell, which is greater than the threshold value. If the signal strength cannot be maintained above the threshold value, a handover process must be initiated in cellular cell space i.e;

$$RSS_{strength_j} \geq RSS_{strengthMin_{ij}}$$

$$PE_{Signal_{ij}} = RSS_{strength_j} - RSS_{strength_i} \geq H_{Threshold_{i,j}}$$

where  $RSS_{strength_j}$  and  $RSS_{strength_i}$  are the average received signal strength from neighbour cell  $j$  and serving cell  $i$ ,  $PES_{ignal_{i \rightarrow j}}$  is the paging expenditure of neighbour cell  $j$  w.r.t. to serving cell  $i$ ,  $RSS_{strength_{Mini \rightarrow j}}$  is the Handover signal strength constraint and  $H_{Threshold_{i \rightarrow j}}$  is the handoff limit the adjacency.

### **b. Fuzzy Logic Based New Call Admission Policy**

Fuzzy logic control has been proposed as it is affected by a diffusion-based load balancing and sharing approach<sup>154</sup>. The objective is to reduce the CBR ratio in the desired cell. This implementation involves in between handoff limits for each pair of neighbouring cells, where the rise in CBR is calculated by taking into account the difference between the CBR of the neighbouring cells and the current handoff margin value. By definition, the CBR is defined as:

$$CBR = \frac{N_{offered}}{N_{blocked}} \quad (2.12)$$

where  $N_{blocked}$  is the number of blocked calls and  $N_{offered}$  overall number of offered calls in particular cell network respectively. The rise in the handover limit indicates the same magnitude, but its sign indicates the direction of the signal strength of both neighbouring cells with balance stability. The handoff limit is limited to a variable time frame to prevent network fluctuations caused by too many parameter changes. The difference in the call blocking rate between the two neighbouring cells is fed into the FLC. To maintain a balance between two adjacent cells, the handoff threshold limit must be continuously changed. To adjust the call blocking rate imbalance between any two adjacent cells, a continuously changing handoff limit must be achieved. This is completely different from previous cases, where minor changes would result in a larger negative effect due to the involvement of too many parametrical changes. Therefore, one additional FLC input in the current handover limit will help to reduce the magnitude and the slide change in the threshold limit will convert it to a negative value.

### c. Neuro-Fuzzy Reinforce Learning

The reinforcement learning process is an intelligent model of learning based on trial and reward (gain or loss)<sup>155</sup>. The fundamental concept of reinforcement learning is that a learning system can be developed to solve complex problems through repeated interactive processes with environmental interactions, as illustrated in Figure 2.14. The reinforcement learning process involves the learning of Q values (s) in a state action set, the value of which would be the maximum-min discounted reward-penalties that can be achieved by the initial step of states, performing action a, and adhering to some optimal policies. This state action set is composed of discrete elements and has a separate value for each action. Here, the reinforcement learning implementation via neural network would be able to solve the call drop problem in a cellular network.

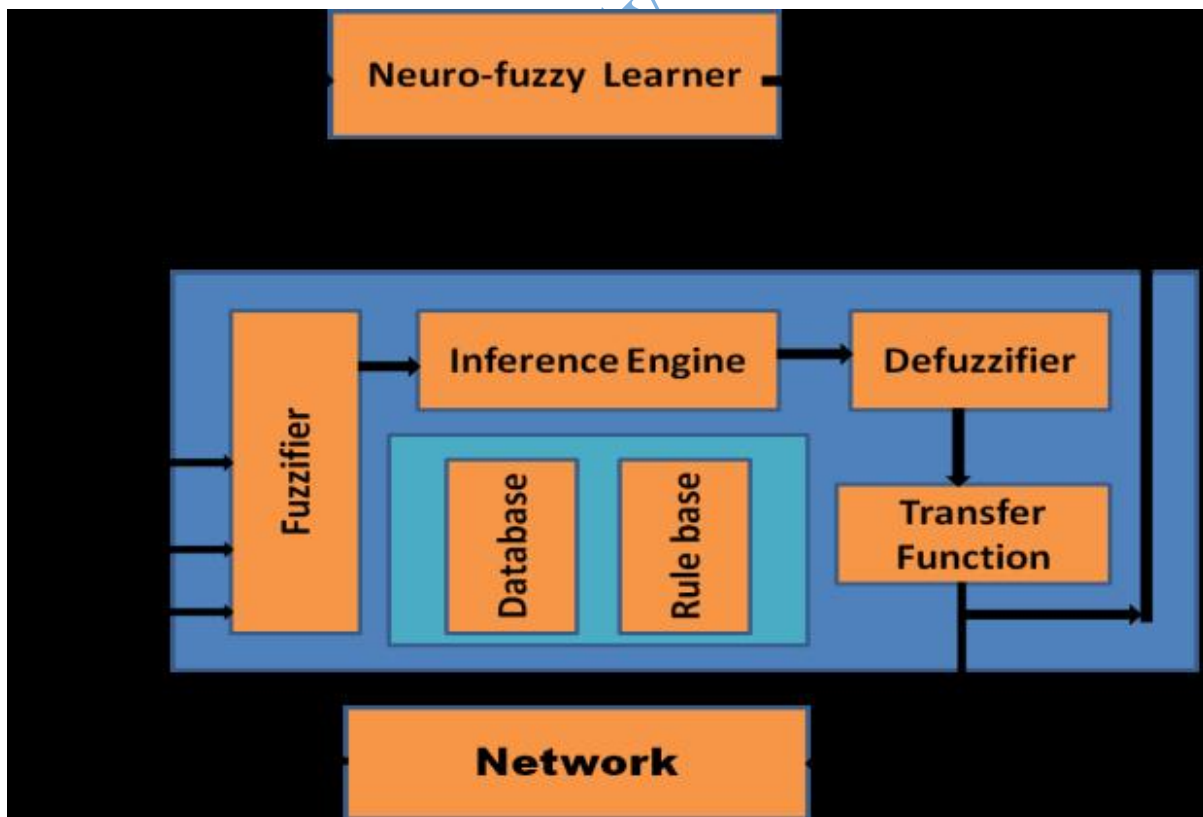


Fig. 2.14 Fuzzy Logic Control Based Design<sup>155</sup>

A Fuzzy Logic Control Reinforcement Learning technique that develops a sequence of actions among selected rules to maximize its adoption learning process for subsequent new steps. Participants have different approaches for a given rule to apply based on prior experiences and certain situations that they have no choice but to respond to with a corresponding rule. In such a case, the consequences are evenly distributed in an output interval.

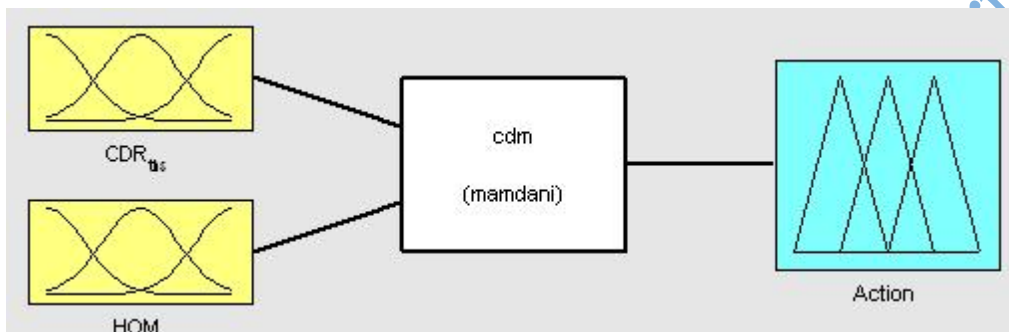


Fig. 2.15 Fuzzy Inference System<sup>156</sup>

## 2.20 Overview of Mobile Network Congestion

Congestion is a widespread issue that is being addressed by GSM service providers<sup>157</sup>. It is a condition in which there is an excessive amount of traffic, as a result of too many items or people attempting to access a resource that is not available. This congestion can be defined as the unavailability of the network to the subscriber when making a call, or when the network is blocked and there is no free path for an offered call<sup>158</sup>. Network congestion is a state in which a network element, such as a switch, concentrator, cross-connect, or transmission link, is unable to meet the agreed network performance objectives for existing connections or new connection requests. It is also a condition in which performance is degraded due to the overuse of network resources, including communication links, processors, and memory buffers<sup>159, 160</sup>. When the number of calls originating or terminating from a network exceeds the capacity available at a given time, it can lead to a queueing of call signals on the

transmission channel, resulting in a decrease in the rate of voice signal transfer, distortion of signals received, or both<sup>161</sup>. In the current situation in Nigeria, there is a heightened focus on quality of service rather than coverage, leading to a proliferation of complaints about dropped calls and congestion<sup>162</sup>.

The term "congestion" is used to describe a situation in which an offered call is blocked and there is no free path for the subscriber to connect to the desired subscriber<sup>162</sup>. This is when the subscriber is unable to make a connection to the desired subscriber in a timely manner<sup>163</sup>. The optimal telephone system is one in which all subscribers can converse in pairs at the same time<sup>164</sup>.

The four components of congestion are Traffic Channels Congestion (TCHC), Dedicated Control Channel Congestion (DCHC), Common Control channel Congestion (CCCHC), and Pulse Code Modulation Congestion (PCMC)<sup>165</sup>.

Congestion can be caused by a variety of factors, such as inadequate radio channels and infrastructure, the inability to accommodate the large number of subscribers on a network, the redialling of subscribers in the event of blocking, the presence of too many users, marketing strategies and pricing schemes and the use of existing equipment facilities rather than new ones.

The Global System for mobile communication (GSM), particularly as customer numbers increase, is facing a number of issues that necessitate ongoing research to enhance network performance. One of these issues is network congestion, which is a major challenge for GSM providers as subscribers grow and new services become available<sup>166</sup>. All proposed techniques for congestion control are based on two principles: either rejecting excessive traffic to avoid over-consumption of network resources, or redirecting excess load in the event of overload. However, these techniques do not provide an explanation for how network resources can be used to absorb refused or diverted traffic, thus preventing revenue loss during congested

periods and thus not effectively addressing congestion during busy hours<sup>167</sup>. Congestion control is the set of measures taken by a network to reduce the amount, intensity, propagation, and duration of congested traffic. It is this aspect of a network protocol that determines how the network responds to congestion<sup>168, 169</sup>. The following optimization models have been proposed to address the issue of congestion on GSM networks in Nigeria:

Government and corporate organizations in collaboration with GSM operators using Dynamic Half Rate Decoder, National Roaming Agreement, Regionalization and the Emerging GSM Networks.

The call classification system divides calls into distinct categories based on the type and scope of the services provided. These categories include Special Voice, Handover Voice, Retrial Voice and New Voice.

A Combined Model for the management of congestion in GSM networks based on call priority, handover call buffer and frequently recent call concepts<sup>171</sup>. This Combined Model is used to evaluate the performance of GSM networks in a comprehensive manner, utilizing the key performance indicators such as call set-up success rate (CSSR), call drop rate (CDR), call completion success rate (CCSR), and traffic channel congestion rate (TCHCR) to compare the performance of the Combined Model with the current system based on the Mobile Cellular Network. The implementation of this model has been found to have a positive impact on the Quality of Service (QoS) of the Nigerian telecommunications sector. Subsequently, the NCC was established as a regulatory body, and since then, the NCC has been in charge of issuing telecommunications licenses to private telephone operators, allowing them to provide telephone services. However, congestion is a major issue for most GSM network providers, as it has a negative impact on the service level agreement due to the inability to make or receive calls in areas with no or weak network signals<sup>172</sup>. The strength of a receiver signal or transmitted signal from a mast or antenna is determined by Coulomb's

law. Coulomb's law states that the force between two points is equal to the product of their charges and is inversely related to the distance between them. This implies that the power of a receiver signal ( $P_r$ ) is equal to the reciprocal of the distance squared from the nearest antenna<sup>173</sup>.

Network congestion is a condition in which the network is transmitting or carrying more data than is able to be accommodated by the system's capacity. For instance, when the number of outgoing or incoming calls from a specific network exceeds the capacity of the network at a given point in time. In a region without a network, it may be challenging to make and receive calls if there is a network but it is not well connected. Conversely, poor call connectivity can be attributed to a number of variables that influence network quality, including congestion<sup>174</sup>. In a BS, congestion occurs when there is insufficient space in the queues to accommodate new arriving packets, resulting in the loss of these new packets. This causes the packets already queued to wait longest in the queue before being transmitted, thus introducing unacceptable packet delays. Performance indicators used include Traffic, Call Setup Success Rate, Handover Success Rate, Standard Dedicated Control Channel and Traffic Channel Congestion. The analysis demonstrated the system's capacity to accommodate high offered traffic without additional resources<sup>175</sup>. The Paging, Signaling and Traffic Channel Model is a model that combines simulations of paging, signalling and traffic channels to explore the most efficient dimensioning of a single physical resource distributed across multiple logical channels and multiple traffic

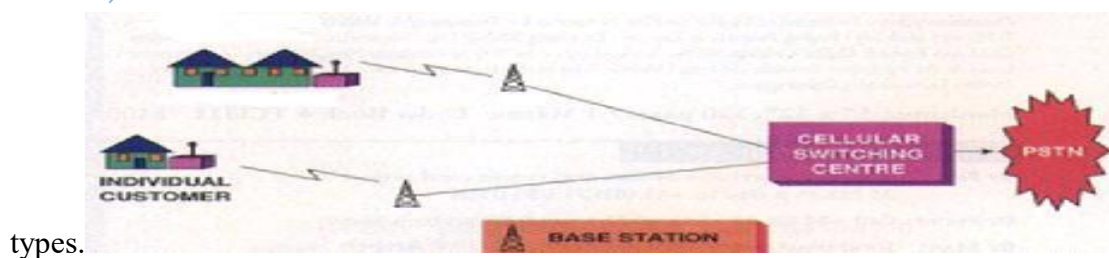


Fig 2.16 Architecture of a Base Station<sup>176</sup>

## 2.21 The Tor Network

As the demand for online privacy continues to grow, Tor has become an indispensable tool for applications that necessitate anonymity on the internet. Tor is a network overlay that utilizes the routing principle to achieve anonymity by tunneling user data through a network, known as a circuit, over a sequence of relays<sup>177</sup>. Onion routing guarantees that each hop in a relay only knows the immediate predecessor and successor, meaning that destinations cannot determine the origin of the communication streams they receive. Typically, clients select a sequence of three randomly selected relays to construct a circuit. Volunteers contribute the necessary resources (such as service and bandwidth) and are not regulated by a central authority.

## 2.22 Causes of Network Congestion

Network congestion is a condition in which a network is unable to cope with the volume of traffic passing through it. Generally, network congestion is a temporary condition in a network and not a permanent condition. However, there are instances where a network remains congested, indicating that a more serious underlying problem is present. This section will outline three of the most frequent reasons for network congestion, including over-subscription, poor network design/configuration, over-utilized devices, and more.

- **Over-Subscription:** Have you ever noticed that certain web browsing times are consistently faster than others? For example, browsing during the day is significantly more enjoyable than browsing at night. This is due to the fact that more users are on the network during peak time (peak time) compared to off-peak period (peak time). This is analogous to riding the train when commuting to work rather than during rush hour. This phenomenon is commonly referred to as over-subscription. Over-subscription occurs when a system (such as a network) is able to handle more traffic

at one time than it was intended to. It is important to note that this is often done intentionally to save money.

- **Poor Network Design/Mis-Configuration:** Network congestion is more likely to occur due to poor design or device mis-configuration. For example, a broadcast storm is a situation in which a large amount of broadcast or multicast traffic is observed on a network in a short amount of time, resulting in significant performance degradation. Broadcast storms are caused by the retention of broadcasts within subnets. The larger the subnet size, the more significant the impact of the broadcast storm. Consequently, a network with large subnets and insufficient consideration for broadcast storms can lead to network congestion.
- **Over-Utilized Devices:** The primary objective of a firewall, switch, or router is to manage a specified amount of network traffic; this is the theoretical capacity; in a production environment, the capacity is likely to be significantly lower. Bottlenecks are another issue associated with over-used devices that may lead to network congestion. It is essential to ensure that the higher level device is able to manage all traffic originating from the lower level devices, as in other hierarchical architectures where multiple devices feed into the higher level device; failure to do so may result in the higher level device becoming a bottleneck and potentially leading to network congestion.

### 2.23 Queuing Network

The Multi Queued, Multi-Server/Channel Queue Network is the queuing system that will be utilized to implement the Priority Queue discipline. This network will consist of seven distinct queues, each of which will have its own priority level. The priority level of each queue will be represented by an associated probability value, which indicates the likelihood of a channel being allocated to a call initiated from that particular priority queue.

## **2.24 Network Congestion Prediction**

Network congestion prediction is a pressing topic that has recently captivated the computer network community. Network traffic forecasting is a widespread problem that is essential for network monitoring, security, congestion prevention, and improved network performance. Various techniques are employed by researchers to predict network traffic<sup>178</sup>. These techniques can be categorised into four broad categories: Linear Time Series Model, Nonlinear Time Series Model, Hybrid Model, and Decomposition Model.

## **2.25 KPIs Benchmark by Nigeria Communication Commission (NCC) for MNOs**

In Nigeria, the Nigerian Communication Act (NCC) is the primary regulatory framework for the telecommunications sector. The NCC is responsible for the licensing of telecommunications operators, the regulation and supervision of their operations, the protection and satisfaction of mobile users' needs. The NCC has formulated regulations on quality of service and Nigerian communications regulations for all telecommunications providers to adhere to in order to satisfy mobile network users' requirements. The following key performance indicators (KPIs) and minimum standards for data communication are included in the Nigerian Communication Act: call setup time, call drop rate, call setup failure rate, call setup success rate, call completion success rate, data rate, latency, and data throughput. Tables 2.1 and 2.2 shows Nigeria communication commission regulations on QoS issued to telecommunications service providers and minimum industrial standard for data communication.

Table 2.1: KPIs parameters considered by Nigeria Communication Commission Benchmark for Mobile Services.

S/N	KPIs	STANDARDS
1	CST	≤6s for local/international call
2	CSSR	≥98% of attempted calls
3	CSFR	≤10% of the attempted calls
4	CDR	≤1% of the attempted calls
5	CCSR	≥97% of the attempted calls

Source<sup>178</sup>

Table 2.2: Industrial Standard for Data Communication.

S/N	KPIs	STANDARDS
1	Data Rate	500-5000kbps 3G, 1-50Mbit/s 5G
2	Latency	100-500ms 4G, <100ms 5G
3	Data Throughput	3.1mbps 3G, 10-300 mbps 5G

Source<sup>178</sup>

### 2.25.1 Quality of Service in GSM Networks

The definition of Quality of service may differ from one situation to another and from one individual to another. Generally, Quality refers to the level of quality of a service when compared to other similar services. Quality of Service is the description or assessment of the total performance of a service (e.g. telephony, computer network or cloud computing service) particularly the performance observed by the network users<sup>180</sup>. Several related aspects of a network service are often used to measure quality of service quantitatively<sup>181</sup>. The definition of Quality of Service (QoS) varies, but in general it is a measure of whether the perceived service delivered meets, exceeds, or fails to meet the expectations of the subscriber. It is

essentially the level of guarantee of service to the user. In contrast, the definition of QoS from the user's perspective is the difference between the Mobile User's expectations and the service provided, or the extent to which the service meets or exceeds the opportunity<sup>182</sup>. QoS is therefore the difference between the expectations of the Subscriber and the service provided by a service provider. Fundamental elements of QoS include absence of interference or tones on the circuit; good quality speech; proper loudness point; high signal strength; minimum call blocking; minimum call dropping; maximum handoff; and good data rates in multi-media applications<sup>183</sup>. However, all of these elements have not been fully achieved within the Telecommunication system, making a successful call uninterrupted is a dream of all mobile subscribers<sup>184</sup>. However, this was not possible due to the poor quality of service experienced by the mobile users.

#### **2.25.2 Quality of Service Estimation Perspectives**

Qualified Service Operations (QoS) for wireless mobile services can be divided into four distinct sub-sectors. These sub-sectors are the planned QoS, the desired QoS, the Service Provider's QoS, and the perceived QoS of the Mobile Users<sup>185</sup>.

#### **2.25.3 Quality of Service Planned by the Mobile Service Providers**

The mobile service provider typically defines the Quality of Service (QoS) that it intends or intends to provide to mobile users, but it is communicated through QoS assessments that are attributed to particular QoS parameters<sup>186</sup>.

#### **2.25.4 Quality of Service Required by the Mobile Users**

This indicates the Quality of Service (QoS) levels that mobile users anticipate or require from a mobile service provider. The requirements or expectations can be expressed in technical terms through descriptive terms that the service provider must convert into QoS parameters that are appropriate for the service<sup>186</sup>.

### **2.25.5 Quality of Service Achieved by Service Providers**

This is achieved through the implementation of certain key performance indicators (KPIs) evaluated and collected from the network. These KPIs are related to the level or stage of quality achieved and delivered to Mobile Users. This is demonstrated through the rates attributed to certain specific aspects of Quality of Service (QoS)<sup>187</sup>.

### **2.25.6 Quality of Service Perceived by the Mobile Users**

The Quality of Service (QoS) of a mobile user is an indication of the quality of the service they have received or experienced. This is typically expressed in terms of the level of approval, rather than in technical terms. Consequently, the QoS of a mobile user should be interpreted as Quality of Service factors to fit other perspectives. Key Performance Indicators (KPI) used to evaluate and estimate the Quality of Service claimed by a mobile user for their mobile service provider should be taken into account as it has a significant impact on the user experience and expectations<sup>187</sup>.

### **2.26 Measurement of Quality of Service**

Qualified Operational Support (QoS) is the assessment and monitoring of the Mobile Network to determine whether the desired value specified by the Telecom Regulatory Entity (TEA) and Wireless Mobile Network Planned (WMP) is achieved and delivered to mobile users. Additionally, three of the factors that are taken into account in the evaluation and monitoring of the Networks' performance are subject to regular adjustment as the coverage and capacity requirements increase. These three are Network Accessibility (NA), Network Retain-ability (NR) and Connection quality (QC) and the fourth factor is Network Coverage<sup>186</sup>.

In order to measure and evaluate the performance of certain factors, a test or assessment is conducted on matrices known as key performance indicators. These metrics include, but are not limited to, call set-up time (CST), call set-up success rates (CSSR), call completion

success rates (CCSR), call drop rate (CDR), Call set-up failure rate (CSFR), and handover failure rate (HFR)<sup>186</sup>.

### 2.26.1 Call Setup Time

Call setup time is a key performance indicator (KPI) that measures the length of time it takes for a call to be established between users. It is defined as the time taken for a user to lift their handset to initiate a telephone call, followed by the time it takes for the call to be transmitted. For example, if a user spends 8 seconds before being connected, the quality of the service is likely to be poor. The longer a subscriber spends accessing the network before making a call, the poorer the service, and the shorter the time the subscriber spends accessing the service, the more satisfactory the service.

$$\text{CST} = T_2 - T_1 \quad (2.13)$$

where  $T_1$  is a point of time where the subscriber presses the send button on Mobile Station (MS) and  $T_2$  is a point of time where connection is established.

The causes of a low or inadequate call setup time during the call making process can be attributed to a variety of factors which includes inadequate coverage, low bandwidth transmission power, low signal strength for downlinks or uplinks, a lack of a top-notch server, antenna issues, faulty hardware units, bad dimensioning, radio interface congestion, and the effects of interference and fading<sup>189</sup>.

### 2.26.2 Call Setup Success Rate

Call setup success rate (CSSR) is a key performance indicator (KPI) that measures the degree of ease with which a call is connected by a mobile user. CSSR is determined by the number of calls made to a given dialled number, with a lower value indicating a more difficult connection, while a higher value indicates an easier connection for mobile users. For instance, a CSSR of 85% indicates that only 85 out of 100 call attempts made by a mobile user are successful, with the remaining 15 being unsuccessful and blocked or dropped. According to

the Telecom regulatory organ (NCC), NCC has established a satisfactory value of more than 98% ( $\geq 98\%$ ) of all attempted calls for both local and national GSM operators. CSSR is calculated using the expression:

$$\text{CSSR} = \frac{\text{Number of unblocked Call attempts}}{\text{Number of attempted calls}} \times 100 \quad (2.14)$$

$$\text{CSSR} = (1 - \text{blocking probability}) \times 100 \quad (2.15)$$

The causes of a low or inadequate call setup success rate in a cellular network include poor coverage, faulty hardware units, poor dimensioning, radio interface congestion, interference and fading, high antenna position, increasing traffic demand, congestion in the network and low handover activity<sup>189</sup>.

### 2.26.3 Call Setup Failure Rate

This Key Performance Indicator (KPI) quantifies the frequency at which mobile service users unexpectedly fail to connect calls during the pre-connect process. The greater the CSFR value, the more challenging it is for the user to successfully connect a call. For instance, a CSFR value of 15% indicates that out of 100 call attempts made by a mobile user, 85 attempts are successful, while the remaining 15 attempts are unsuccessful.

It is expressed as:

$$\text{CSFR} = \frac{\text{Number of failed Call attempts}}{\text{Number of attempted calls}} \times 100 \quad (2.16)$$

The causes of call setup failure in a mobile network cell include poor coverage, inadequate dimensioning, low signal strength, faulty hardware units, radio interface congestion, CM service rejections and TCH failure assignments<sup>189</sup>.

### 2.26.4 Call Drop Rate

Call drop rate (CDR) is a key performance indicator (KPI) that measures the network's inability to maintain an ongoing call when it is connected by a GSM Subscriber. It is the proportion of calls that are terminated before the speaking parties have completed their conversational tone or before one of them hangs up. For example, a CDR of 7% indicates that

for every 100 connected calls, seven (7) calls will be terminated before the calling party (Subscribers) terminates the call. The National Communications Commission (NCC) has established a satisfactory value of less than 1% ( $\leq 1\%$  of attempted calls) for local and national GSM operators. The indicator (CDR) can be calculated using the expression:

$$\text{CDR} = \frac{\text{Number of dropped Calls}}{\text{Total number of attempted calls}} \times 100 \quad (2.17)$$

$$= (1 - \text{Call Complete probability}) \times 100 \quad (2.18)$$

The occurrence of call drop in mobile networks can be attributed to a variety of factors, including a low BTS power output, a lack of a top-of-the-line server, a poor quality connection or uplink, antenna issues, a malfunctioning mobile station battery, a too high timing advance, congestion in adjacent cells, an unsuccessful outgoing handover, and an unsuccessful incoming handover<sup>189</sup>.

#### 2.26.5 Call Completion Success Rate

The call completion success rate (CCSR) is a key performance indicator (KPI) that measures the rate at which both users of a mobile network initiate, get connected and complete a call. It is the ratio between the number of calls successfully completed and the total number of calls attempted. This ratio is usually expressed as a percentage or decimal fraction. CCSR is a KPI parameter that is taken into account when assessing Network Retainability, as it is a measure of Customer Satisfaction. For example, a CCSR of 95% indicates that only 95 of the 100 call attempts made by the mobile user are successful, with the remaining 5 unsuccessful. The National Communications Commission (NCC) has set a standard of more than or equal to 95% for local and national calls as a satisfactory value for all GSM operators. The KPI can be calculated using the expression:

$$\text{CCSR} = \frac{\text{Number of completed Calls}}{\text{Total number of attempted calls}} \times 100 \quad (2.19)$$

### 2.26.6 Data Rate

Data rate is defined as the rate at which bits per second are transmitted over a channel. It is the rate at which information is transmitted within a computer system or between a computer and a peripheral device, expressed as bytes per second (Mbps). According to<sup>190</sup> of the Federal Communications Commission (FCC), data rate is affected by a variety of factors, such as the data transfer technology used, other users, and poor coverage.

### 2.26.7 Latency

Latency is the rate at which data is transmitted from a source to a destination. It is a measurement of the delay it takes for the data to reach its destination across a network. Generally, it is measured as a "round trip delay". According to Wireless World, a network's latency can be calculated mathematically.

$$\text{Network Latency} = \text{Propagation delay} + \text{Serialization delay} \quad (2.20)$$

$$\text{Propagation delay} = \frac{\text{Distance}}{\text{Speed}} \quad (2.21)$$

$$\text{Serialization delay} = \frac{\text{Packets size (bits)}}{\text{Transmission Rate (bps)}} \quad (2.22)$$

### 2.26.8 Data Throughput

Throughput is a measure of the actual performance of a system, when delay is taken into account, or the rate of successful delivery of messages across a communication channel. The term "throughput" is often used to refer to the quantity of products or services a company is able to produce and provide to a customer in a given time frame.

The primary reasons for low throughput are inadequate coverage, availability issues, uplink interference, downlink interference, problematic users equipment, transmission instability and bottleneck, accessibility issues, high radio errors and link adaptation.

## **2.27 Factors Affecting Quality of Service**

The service provided by the mobile network providers involves generation, transmission and reception at different points and therefore not free from hitches. There are many factors that affect the QoS provided by the service Providers in Nigeria. Some of these factors are:

### **2.27.1 Bandwidth Allocation**

The Quality of Service (QoS) of wireless mobile communication is heavily influenced by the utilization of bandwidth, which is defined as the maximum rate at which data can be transmitted across a given route<sup>191</sup>. Bandwidth can be divided into three categories: Network bandwidth, Data bandwidth and Digital bandwidth. An example of a bandwidth allocation problem is when a telecommunications operator experiences an excessive number of Mobile subscribers, resulting in a lack of channels to route calls through. This can lead to call setup failures or congestion and queueing in the network, thus impacting the Quality of Service provided by wireless telecommunications providers<sup>192</sup>.

### **2.27.2 Handover Failure in Mobile Communication**

In wireless mobile communications, a handover is the automatic switch of a call from a cell to another within the same base station, or from a base station to a different base station, without interrupting or ending the active connection. During a call, handover is the process of changing the channel associated with the current connection. It typically begins with either a cell boundary crossing or a decrease in signal quality in the current channel. On the other hand, in wireless mobile communication, handover failure occurs when the mobile station is moving and does not transfer an active call from the same cell to another base station or to another base station, resulting in an interruption of an ongoing connection.

### **2.27.3 Call Setup Failure**

Call Setup Failure (CFF) is a phenomenon that can occur in telecommunication systems when a mobile user connects to a call, and access is granted, but the call cannot be

established successfully, thus impacting the Quality of Service (QoS). In theory, when a mobile call is set up, the communication call is assigned from a separate dedicated channel to a Traffic Channel (TCH). However, if the TCH chosen is affected by cross talk, the mission will resolve to fail, and the Assignment Failure Communication will be transmitted to the MSC. After this, the task will be re-established. CFF is a key performance indicator (KPI) used to assess Network performance to identify network accessibility, and is therefore one of the primary factors that influence the Quality of Service in Telecommunication systems<sup>193</sup>.

#### **2.27.4 Call Retention**

The phenomenon of call retention in telecommunication systems is when a call is automatically held by a Mobile Service Provider after being initiated and established while the conversation is still taking place. This simply indicates the length of time a mobile user holds on a mobile network following the connection of a call. However, if the conversation terminates while the call is still in progress, it is referred to as a drop call. A dropped call is a situation in which a call that has been connected is unexpectedly terminated while the conversation is taking place. This is a common occurrence in Nigeria's telecommunication system, as conversations are terminated unexpectedly while they are still taking place. Call retention, or the capacity to hold calls, is one of the key performance indicators (KPI) that are taken into account when assessing Network Retainability in the wireless telecommunication sector, and is therefore one of the main KPI factors that influence Quality of Service (QoS) in the telecommunications system<sup>194</sup>.

#### **2.28 Wave Propagation Effects and Parameters**

A wireless mobile network signal is emitted or transmitted by a Base Station (BS) or a transmitting antenna in the form of Electromagnetic Wave or Field (EMF). These signals are exposed to a wide range of natural environments and are designed to traverse a variety of terrains. It appears that the transmission environments of these signals are affected in one

way or another, resulting in a range of variations in the mobile signal level transmitted and the unstable signal coverage received, as well as the quality of the network provided. These parameters include Free Space Loss, Signal fading and Interference.

### 2.28.1 Free Space Loss

Free space loss is a condition or phenomenon in which a signal transmitted by a Base Station undergoes degradation and diminution during transmission in a free space environment prior to reaching the MS or the receiving antenna. Free space loss is the loss of signal power of electromagnetic waves resulting from a linear path through a free space environment, where there are no obstructions in the vicinity that would cause reflection and diffraction<sup>195</sup>.

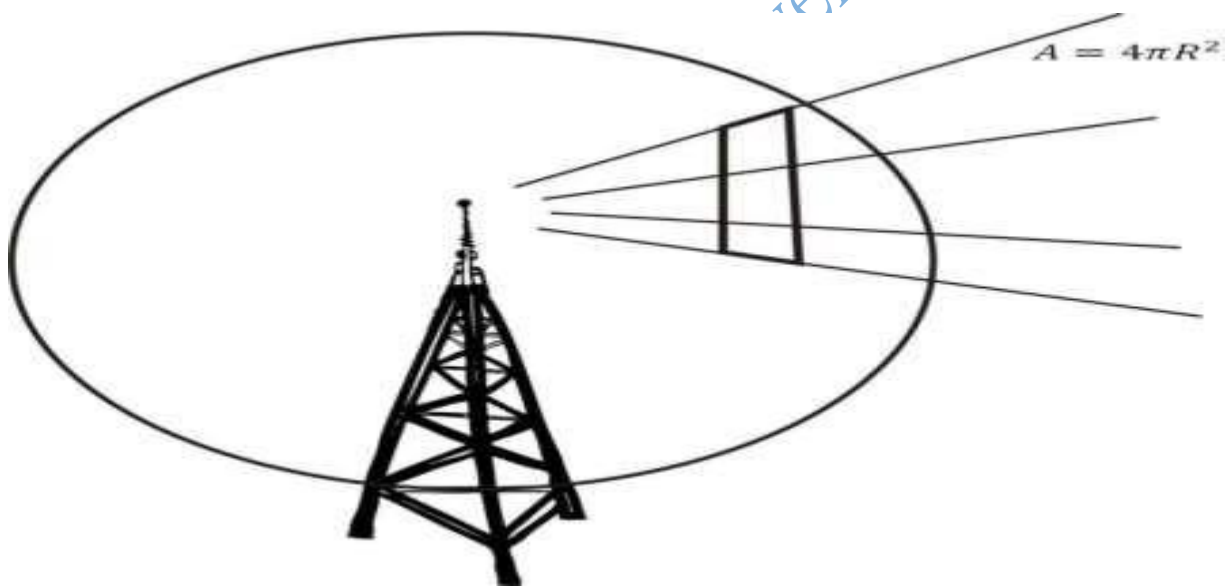


Figure 2.17 An Isotropic Antenna Radiating EMF <sup>196</sup>

### 2.28.2 Fading of the Signal

The signal strength of the transmitted signal decreases as it moves from the transmitting antenna to the receiving antenna. This may be caused by a trend of path loss or by interference in the transmission<sup>197</sup>.

### 2.28.3 Interference

The phrase "interference with a signal" is commonly used to refer to the presence of unwanted signals on a signal that should be of good quality. This can be caused by obstructions in the signal, which can arise from the transmission of signals from the receiving station over a distance, or from artificial materials<sup>198</sup>. This can lead to a decrease in the quality of service offered by wireless telecommunication providers, as the quality of service is affected by the presence of interference in either the broadcast or the received signals.

### 2.29 Maintaining Good QoS in Mobile Communication

Despite the increasing number of wireless mobile customers in Nigeria, service providers must remain committed to providing their customers with superior quality services. The quality products help to maintain customer satisfaction and loyalty, as well as reduce the risk and cost of replacing defective products. By acceding to a recognised quality standard, companies can build a reputation for excellence. Currently, Nigeria is home to four major wireless mobile operators: Airtel, 9mobile, Globalcom, and MTN.

In the meantime, subscribers of mobile services typically lodge complaints through a variety of channels, including telephone calls to customer call centers, visits to customer care units, and visits to or searches on the Network providers' websites.

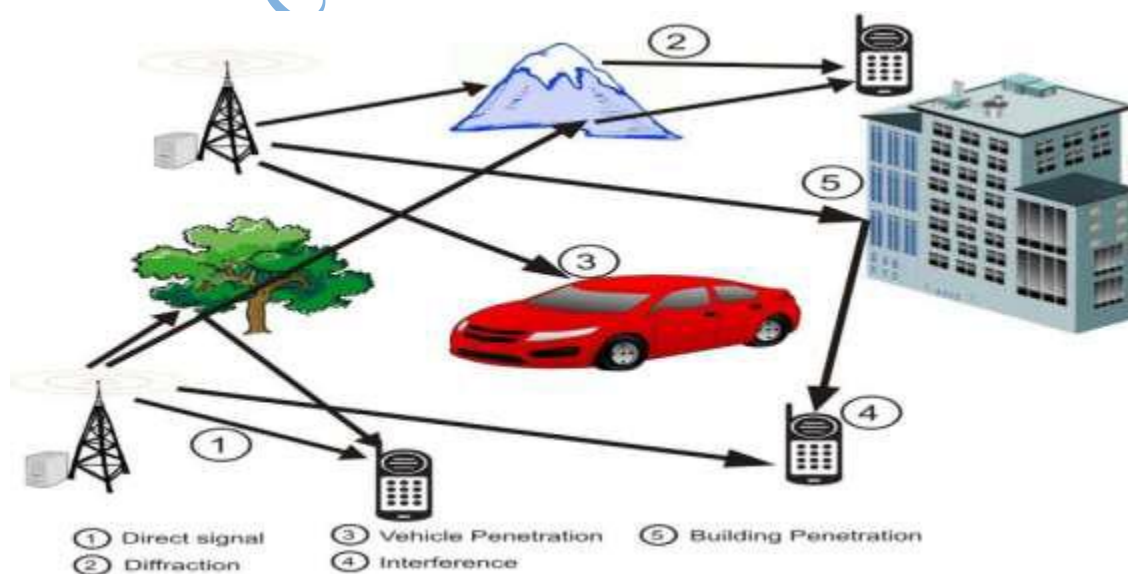


Figure 2.18 Factors affecting Wave Propagation<sup>200</sup>

Prior to making a call, Mobile Users may experience a variety of major issues, such as difficulty making a call, inability to recharge, SMS transmission issues, balance issues, and other related issues<sup>201</sup>.

### 2.30 Wireless Communication System

The mobile communication system consists of a transmitter, receiver, and channel. The transmitter consists of a burst builder, a modulator, an up-amplifier, and a filter. Burst building blocks accept the generated information bits as input and attach special word and guard bits to form a frame structure. Modulation blocks map bits to symbols using generated bursts as input. To generate a continuous, limited band signal that can be transmitted over a carrier frequency band, the modulated signals are processed through the up-amplifier and pulse shaping filter, and the channel should take into account fading effects.

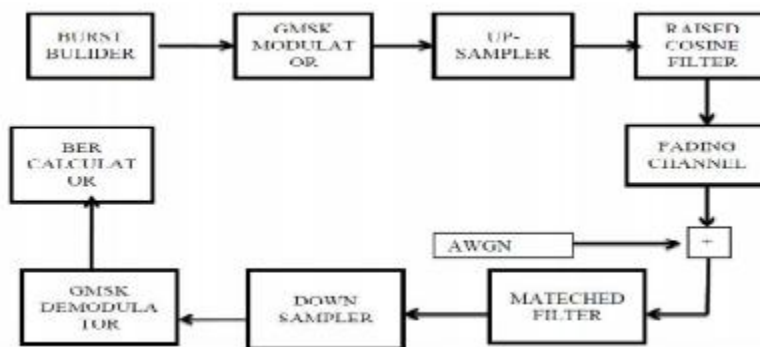


Fig 2.19 Block Diagram of a Typical Wireless Cellular System<sup>202</sup>

Figure 2.19 shows a general block diagram for a wireless cellular system, which is a subset of the GSM network. The design below is also based on this general published framework.

#### 2.30.1 Analysis and Design for Queuing of Handover Calls (e.g GSM)

The objective is to facilitate communication in a smooth and congestion-free manner. The benefits of the system include timely reporting of handover calls in congested network environments to enable maintenance and problem-solving. Figure 2.20 illustrates a use case diagram illustrating the parties involved in the system interaction and their respective

roles.

## User Case Diagram

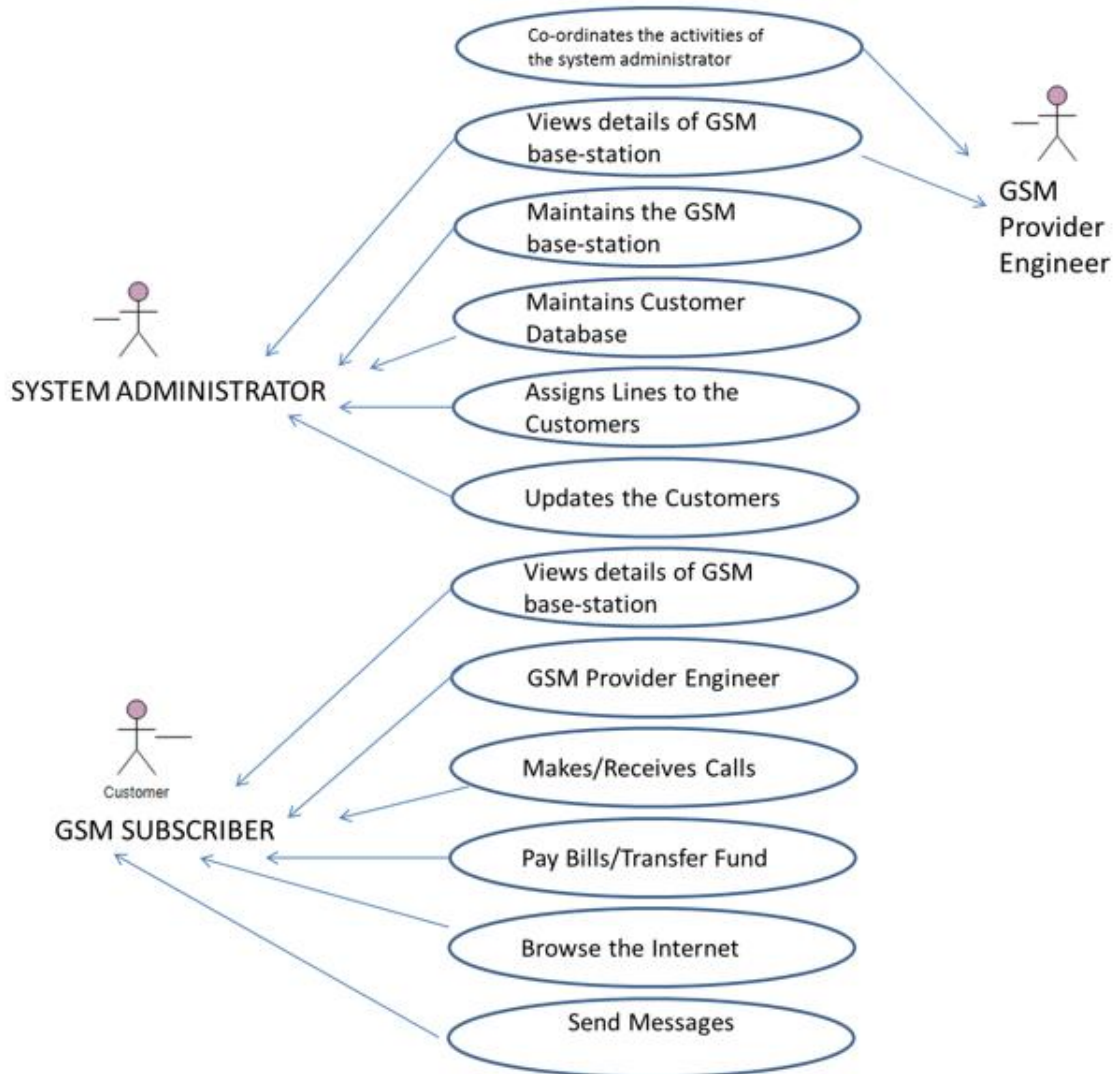


Fig 2.20 Use Case Diagram of a GSM Congestion Monitoring System<sup>203</sup>

### 2.31 Machine Learning

Machine learning is a major sub-field of Artificial Intelligence that is revolutionizing a variety of industries due to its capacity to surpass the capabilities of human experts in automating complex tasks. A machine learning approach, referred to as "deep reinforcement learning" (DRL), is employed to teach computers to learn. DRL is a combination of RL and DL<sup>204</sup>.

In the general category of machine learning, supervised machine learning is the most popular sub-track, followed by unsupervised machine learning, reinforcement learning, semi-supervised learning, self-supervised learning and more. This sub-track is highly adaptable and scalable, making it suitable for a variety of applications and sectors. The main advantage of supervised learning is that a labeled data set is available, allowing the model to learn from both the input and output. For example, a model may be trained to anticipate a future output by sending a future input to a mapping process.

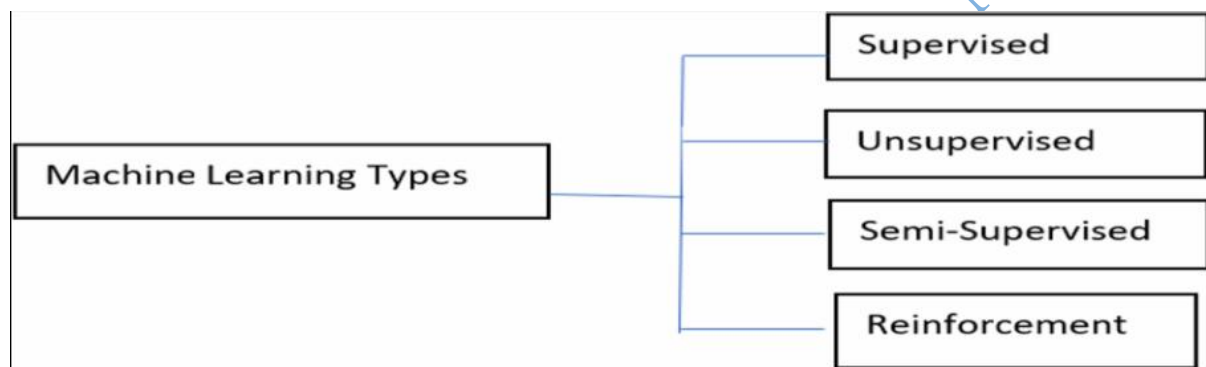


Figure 2.21 Overview of machine learning types<sup>205</sup>.

The two main types of supervised learning problems are those based on regression and classification. In a regression-based problem, the model predicts a continuous value, such as the price of stocks, while in a classification-based problem, it predicts a specific discrete value, category, or class, such as whether the price of stocks will rise or decrease. Discrete values can be any number, as long as the values of the number are known beforehand. For example, a computer vision problem can have a million classes to distinguish, and it is classified. In contrast, an anomaly detection problem is a classification problem, as the model must predict whether a particular point or sequence is abnormal or not. Unsupervised learning is a type of machine learning in which there is no prior knowledge of the output, making the problem of unsupervised learning more difficult. On the other hand, in Natural Language Processing (RL), there is no input or output, and the learning process is dependent on the

agent's interactions with the environment and the feedback signals it receives from those interactions<sup>206</sup>. Self-supervised, one-shot and several-shot learning models are based on the use of both labeled and unlabeled data, with the model attempting to generalize the learning experience using a limited amount of labeled data and augmenting it using unlabeled data. In order to apply unsupervised and supervised machine learning models for anomaly detection, models from both categories have been selected<sup>207</sup>.

Anomaly detection problems are often posed by anomalies that are not labeled as anomalies, which can be transformed into supervised classification problems and then applied to a suitable model to yield good performance. However, this is often not the case, and in such cases, domain experts may be required to label data and provide guidance and instructions for the labeling process. While this may be a cost-effective solution, it can be time-consuming and expensive to have domain experts labelling the data. An alternative solution is to have meta-data or additional information regarding the data set, such as the percentage of anomalies or contamination value. With this information, confidence interval-based statistical approaches can be used to flag the various anomalies based on model performance. This is the methodology to be followed in our thesis, as the anomalies are not identified in our dataset.

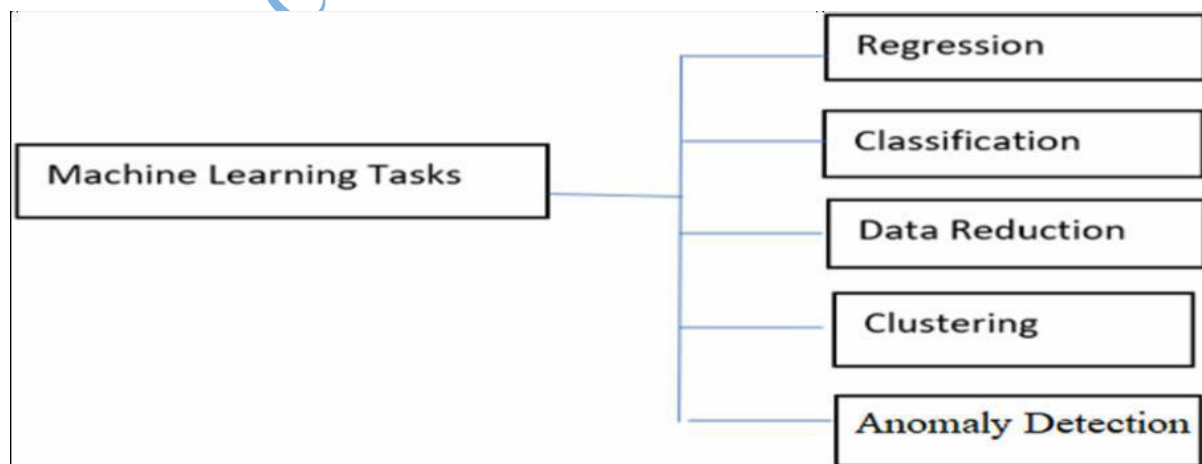


Figure 2.22 Overview of Machine Learning Tasks<sup>208</sup>

Machine learning techniques are applied in numerous areas to solve different kinds of tasks.

Five common tasks are explained as follows:

- **Regression:** Regression, also referred to as value estimation, is the process by which the input features are associated with a numerical continuous variable. Machine learning techniques are employed to minimize the error of the prediction by optimizing the coefficients associated with each independent variable. The output variable can be either an integer or a float-point number.
- **Classification:** Input features are associated with one of the individual output variables based on the classification. An output variable is used to represent the class of the underlying problem. For binary classification, an output variable can be either one or zero, while an output variable for multidimensional classification can have more than one class.
- **Clustering:** Clustering is the process of dividing data points into logical categories. The pattern of similarity between data points serves to unify the data. Clusters of similar points are used to provide data scientists with valuable insights.
- **Data Reduction:** Data reduction operations can reduce the number of numbers due to the presence of noisy data instances or repetitive data points, as well as the deletion of certain rows (data points). Additionally, features that are strongly related or are not of great importance may be removed from the dataset in order to generate models more quickly. Generally, data reduction work is employed as a complement to other machine learning operations, such as regression and classification.
- **Anomaly Detection:** Unsupervised learning techniques are frequently employed to address anomaly detection issues. Anomaly detection techniques are employed to organize the

samples in a manner analogous to that of a clustered algorithm. These methods are employed to identify any anomalies in the dataset.

### **2.31.1 Application of Machine Learning in Telecommunication Industry**

The telecommunications sector generates and stores a vast amount of data, including call detail data, network information, hardware and software component status, and customer information. This vast amount of data necessitates manual data analysis, making it difficult or even impossible to analyze manually<sup>209</sup>. The telecommunications industry is a major determinant of a nation's economic and social development on a global level, and its development is essential for the overall development of all aspects of society, politics, and economics. The telecommunications sector is highly dynamic and Machine Learning is employed for a range of purposes<sup>210</sup>.

### **2.32 Related Works**

Many researches had been carried out prediction models of handover call drops. These are some of the reviewed research papers.

The demonstration of an ANN for the optimal selection of call drops in a GSM network was presented using RSS<sup>211</sup>. The hardware currently available to read the RSS was used to collect and develop RSS parameters over time. Data sets from four different MNOs were obtained and used as inputs and targets for ANN training, testing, and prediction. Simulated parameters were used to demonstrate high accuracy, with 0.99 being the most consistent value. The output regression plots of the graph showed a linear distribution of the selected RSS values compared to the real value results obtained. The developed method was successful in selecting the network optimally.

A DNN model for the purpose of evaluating and predicting traffic activity levels derived from telephone calls, SMS transmissions, and Internet usage was proposed<sup>212</sup>. The model was

able to generate predictions of the traffic activity level and related probabilities that corresponded to the anticipated traffic levels, with an overall accuracy of between 98.6% and 99.8%.

A call drop prediction model in real time cases, taking into account GSM parameters using an Artificial Neural Network (ANN)<sup>213</sup>. The GSM quality of service parameters used in the model are Received Quality (RQ), Bit Error Rate (BER), Received Signal Level (RSL), Timing Advance (TA) and Frame Error Rate (FRR). This model will be useful for telecom operators to conduct surveys and optimize their telecom network in order to reduce the rate of call drops. The use of ANN for the growth of the call drop structure can then be used to predict and classify call drop events in a GSM network. The model was found to be 87.5% accurate in predicting call drop events. This suggests that call drops are not only associated with the strength of the signal or the unsuccessful handover, but also with the parameters of the telecom network that caused the calls to drop.

An optimization model to assess the robustness of a Self Optimizing Network in relation to mobility using an Annular Networking Network (ANN) is used to determine whether drops in calls exist or not in a stable active mode<sup>214</sup>. The ANN was used to predict call drop at handover, with a performance accuracy of 95%. The study examined various parameters of mobility that are responsible for drops in calls during handover, including subscriber speed (meter/second), signal strength (dBm), set of calls (seconds), base station distance (meters), call duration (seconds), latitude and longitude, and the result of a call (1 and 0). The data was collected with the aid of Network Signal Application.

The causes of call drops in telecommunications network networks and proposes potential solutions to address them was examined<sup>215</sup>. Extensive data sets have been collected from telecommunication network operators, including subscribers, network operations, network applications, and real-time call processing. These large datasets offer valuable insights into

business operations. The study employs an LR (Linear Regression) algorithm, which is based on the principle of predictive analysis. Three main benefits of linear regression analysis are the ability to measure the impact of forecasting, the strength of predictors, and the forecasting of trends, with performance accuracy rates of 97.5% and 94%.

Machine Learning (ML) techniques can be employed to anticipate the drop of calls in a real-time network. During the fifth generation of fifth-generation telecommunication networks, operators are utilizing ML techniques to self-organize networks was examined<sup>216</sup>. The causes of the drop in calls can range from a failed handover to capacity and coverage issues. In the current networks, these issues are addressed by analysing key performance indicators, however, these parameters are often not specific to users or services. This study examines the use of machine learning techniques, such as Logistic regression and Neural Networks, to classify the state of links. It also examines the parameters that indicate the connection status of the link, such as the Block Error Rate (BLER), Reference Signal Received Power (RSRP), and other relevant parameter.

Machine learning can be used to predict network issues in the past, particularly to address call drop issues in telecommunications networks<sup>217</sup>. Troubleshooting of telecommunication networks is traditionally a manual task that requires professionals to monitor the network 24 hours a day. This study proposes the development of Troubleshooting Trees, a machine learning software tool that utilizes an unsupervised methodology to automate the detection of performance anomalies in telecommunications networks. This methodology combines several machine learning algorithms, such as clustering and decision tree, to create a tool that requires minimal information and is quickly trained. Experiments conducted on operational cellular networks commercially have demonstrated that Troubleshooting Trees can accurately identify and classify network anomalies.

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## Chapter Three

### Methodology

This chapter examines the research methodology employed in improving call quality for call drops during handover in cellular communication. It outlines the techniques employed to make these predictions. The initial step of the analysis is to employ a simulated data collection methodology to acquire the data used as an example in this study with the aim of training and testing the prediction models.

#### 3.2 Quality of Service Indicators for Network Service Providers

The Call Setup Success Ratio (CSSR), which is the ratio of the unblocked number of calls attempted to the total call attempt, is known as the "Call Setup Success Rate". The "Dropped Call Rate" is the percentage of calls that are terminated prematurely, either by the caller or the called party, and the "Standalone Dedicated Containment Rate" is the rate at which a dedicated control channel cannot be accessed during call setup. Both CSSR and TCCH are measures of the probability of not being able to access a dedicated control channel for voice and data transmission between mobile devices and base stations. Communications in the phone call service segment are much more widely distributed than those in the internet data service segment.

##### 3.2.1 Call Setup Success Ratio (CSSR)

The CSSR is a measure of the percentage of calls that are successfully connected to the desired phone number, taking into account the fact that not all attempts to connect to the desired number are successful due to various factors. It is calculated as the ratio between the number of attempts that are not blocked and the total number of attempts<sup>1</sup>.

$$\text{CSSR} = \frac{\text{Number of unblocked Call attempts}}{\text{Number of attempted calls}} \times 100 \quad (3.1)$$

$$\text{CSSR} = (1 - \text{blocking probability}) \times 100 \quad (3.2)$$

### 3.2.2 Call Drop Rate (HCDR)

DCR stands for "Dropped Call Rate", which is the rate at which a call is terminated before it is typically released by either the recipient or the caller. This rate is calculated as the ratio of the number of calls that are dropped to the number of call attempts<sup>1</sup>.

$$\text{CDR} = \frac{\text{Number of dropped Calls}}{\text{Total number of attempted calls}} \times 100 \quad (3.4)$$

$$= (1 - \text{Call Complete probability}) \times 100 \quad (3.5)$$

### 3.2.3 The Standalone Dedicated Control Channel Congestion Rate

This is the likelihood of not being able to access the SDCCH during the call setup process. The purpose of the SDCCH is to provide a dependable link for signaling and SMS communication.

### 3.2.4 Traffic Channel Congestion Rate (TCCH)

Traffic channel congestion (TCH) is a key performance indicator that affects the performance of a GSM network and customer satisfaction. It is the likelihood of not being able to access a traffic channel while setting up a call for voice and data transmission between a mobile phone and the base station<sup>1</sup>.

$$\text{TCCH (\%)} = \frac{\text{Number of call connect fails}}{\text{Total Number of call attempts}} \times 100 \quad (3.6)$$

### 3.3 Simulation Parameters

Table 3.1 shows the simulation parameters

Attribute	Description	Data Type
total _ available_ channels	Number of channels entered by the user	Numeric
Type_ of_ call	To identify either the call is new generated call	Numeric or String
number_ of_ periods	Number of simulation periods the user entered	Numeric
calls_ accepted	Number of accepted successfully admitted	Numeric
calls_ dropped_ rate	Number of calls rejected	Numeric
total No _of_ calls	Number of all calls admitted and dropped	String
timePeriod	Time taken for a simulation	Numeric
call_ dropping probability	Call dropping probability	Numeric
cell_ tower_ x	Cell Tower in the Network	String
timestamp	Time Information	Numeric
signal_ strength	Simulated Signal Strengths	Numeric
call_ setup_ success_ rate	Rate of Call Setups	Numeric
tch_ 1,tch_ 2	Traffic Channels in the Network	String

(Source: Researcher, John-Dewole T. 2023)

### 3.4 System Models for the Improvement of Call Quality for Calls Drop during Handover in Mobile Communication

System models for the improvement of call quality for calls drop during handover in mobile communication are:

1. First KPIs cells are collected.
2. Next the collected dataset is preprocessed. As a result, training and testing datasets are generated.
3. Using the training set, the LSTM, CNN and Ensemble algorithms is trained to develop GSM identification model.
4. Then using the testing dataset, the trained model is tested.
5. Next the performance of the developed model is evaluated using classification evaluation metrics.
6. If the model meets the required performance criteria, final prediction model for mobile Communication is produced. Unless, the algorithm is optimized by tuning hyperparameters then passes through training, testing, and evaluating steps until the model meets the performance evaluation criteria.

The system model required to build the prediction of network congestion for queuing of call drops in mobile communication is shown in figure 3.1.

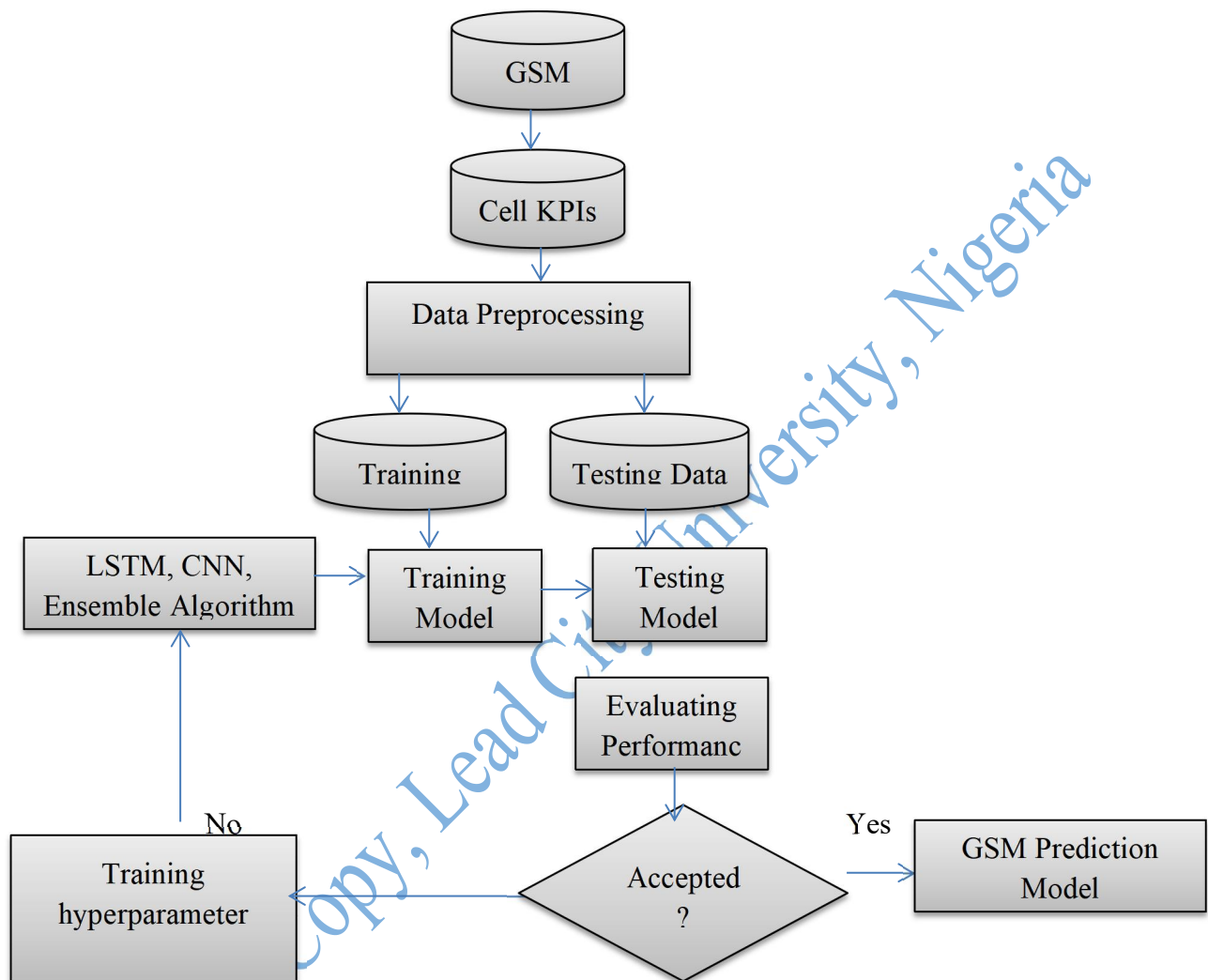


Figure 3.1 System Flowchart (Source: Researcher, John-Dewole T. 2023)

### 3.5 The Research Framework

This section outlines the process of constructing a call drop minimization model. Figure 3.2 outlines the research framework, beginning with the data collection step. The data is then preprocessed by feature scaling, and the dataset is divided into two categories: training and testing. The training dataset is used to construct the model, while the testing dataset is used to validate it. In this study, 70% of the data is used for training the minimization model to make up the ensemble and each model in the ensemble will be trained on the subset of the data and

30% for testing the dataset i.e for evaluating the ensemble performance, which also serves as a validation set to assess how well the models generalizes to new, unseen data.

The model is developed using the training dataset, with the number of layers, optimizers, learning rate, and loss function being identified during the model development phase. This phase is used to design the model structure and adjust the parameters. Finally, the calculated data is scaled back to its original scale to determine the error. The validation step is conducted with the testing dataset, resulting in the optimal model. Finally, the prediction of the time series is conducted using the optimal model.

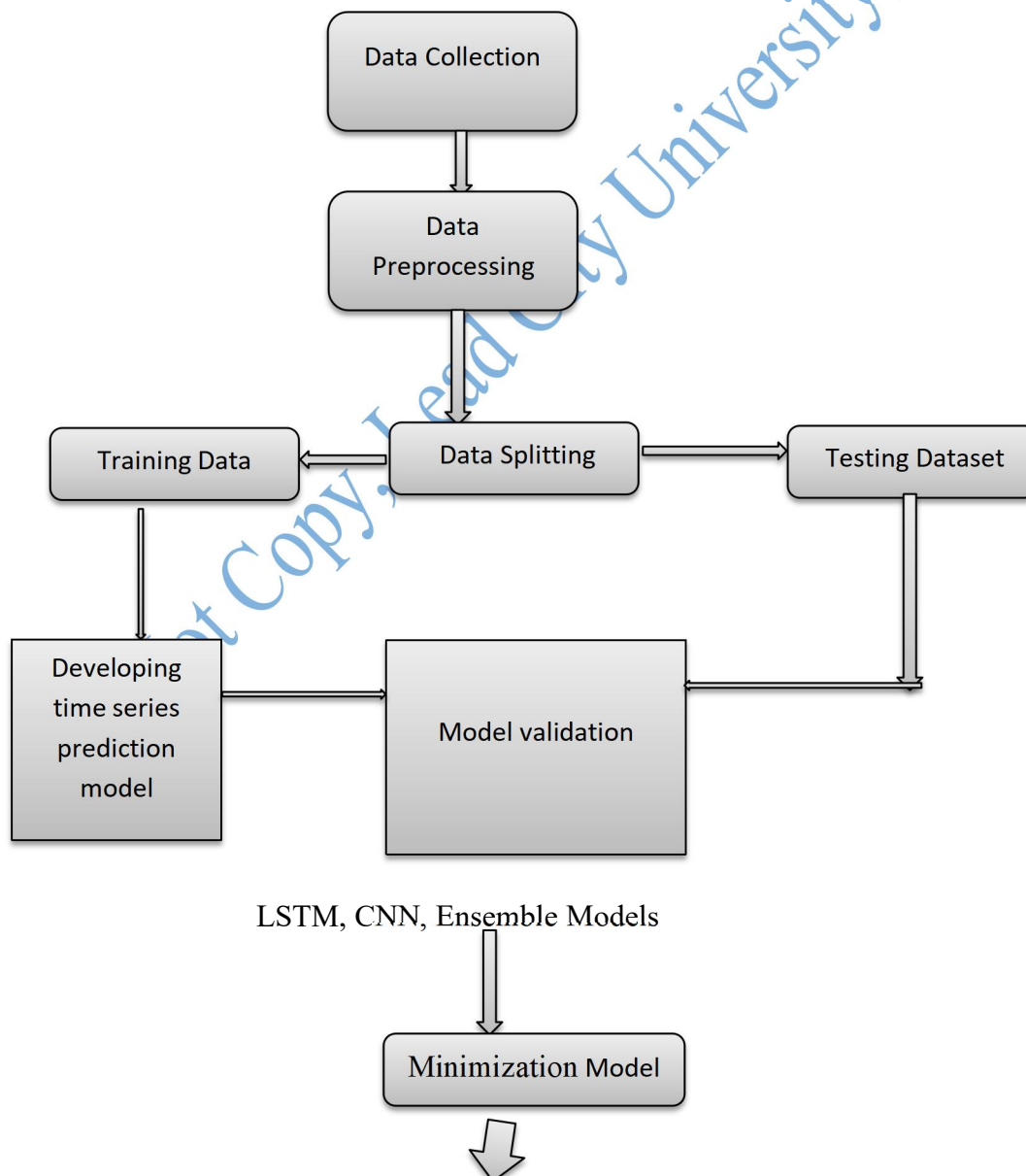


Figure 3.2 The Research Framework (Source: Researcher, John-Dewole T. 2023)

### 3.6 Understanding of the Data

Understanding the data is a crucial step in any machine learning project. In this section, we discuss the data collection, description, preparation, and formatting processes.

#### 3.6.1 Data Collection

The data used in this study was collected from various sources, including real (from the data acquired from National Communication Commission) and simulated telecommunication service providers, network equipment logs, and user feedback which was from a random generalization of synthetic data (secondary data) e.g signal strength, data usage, congestion levels. The dataset comprised network performance metrics and infrastructure information.

To create the minimization models, we collected real-world data from NCC. The data collection process involved accessing call drop rate, call setup success rate, traffic control congestion rate from telecommunication service providers. We also obtained data on the geographical locations of base stations and their corresponding coverage areas, and the steps involved are;

- **Define Geographical Area:** Determine the geographical areas one wants to simulate e.g urban areas.
- **Generate Base Station Locations:** Use random generalization within the defined geographical area, i.e it identifies the coverage requirements of the base station.
- **Signal Strength Assignment:** Simulate signal strength variations within the coverage areas.

- **Data Format:** Organize the generated data in a structured format, including fields for base station location (longitude, latitude) coverage area details, signal strength and network load.

### 3.6.2 Collected Data Description with the Performance Metrics

The data collected encompassed a broad array of characteristics, such as signal strength, duration of calls, type of call, location, day of day and network performance metrics, including throughput, latency, packet loss rates and more. Additionally, timestamps were included for each observation, enabling the analysis of temporal trends. A dataset of 3000 data points covering 30 cell towers was compiled and used, spanning the period from July 1<sup>st</sup> to 10<sup>th</sup> July, 2023, with each cell running for 5 minutes. It is important to note that this table only represents a sample of the full dataset, which consists of 3000 data points spanning 30 cell towers.

Table 3.2 Dataset Compilation (Simulated Data)

Timestamp	Cell_Tower	Signal	Stre	Call	Drop	Data	Usag	Longitude	Latitude	Call_Type	Congestion	CSSR
01/07/2023 8:00	Tower_015	-82	2.998088	207	33.81849	-86.6241	Voice	Low	98.6643			
01/07/2023 8:05	Tower_028	-78	1.820971	230	31.11428	-89.0754	Data	Medium	92.75583			
01/07/2023 8:10	Tower_020	-80	2.78229	203	33.90724	-88.9105	Data	High	93.94189			
01/07/2023 8:15	Tower_014	-88	1.06543	436	32.83883	-88.8066	Data	Low	99.73535			
01/07/2023 8:20	Tower_007	-86	1.165722	381	32.13495	-89.878	Data	Medium	93.60169			
01/07/2023 8:25	Tower_011	-88	2.716815	352	30.71074	-89.6582	Data	Medium	95.69196			
01/07/2023 8:30	Tower_010	-83	1.972199	434	33.55252	-85.8764	Data	Medium	92.05008			
01/07/2023 8:35	Tower_002	-74	1.555191	288	30.8289	-89.8449	Voice	Medium	93.43025			
01/07/2023 8:40	Tower_022	-80	1.07888	267	32.8941	-89.08	Data	Low	90.70681			
01/07/2023 8:45	Tower_024	-87	1.828988	327	34.77104	-85.6043	Voice	Low	97.5629			
01/07/2023 8:50	Tower_016	-80	2.30169	287	31.11163	-85.1446	Data	Medium	93.22861			
01/07/2023 8:55	Tower_021	-77	2.311691	347	31.00937	-87.247	Voice	High	95.67683			
01/07/2023 9:00	Tower_005	-83	1.373318	200	32.59223	-88.3307	Data	High	96.23879			
01/07/2023 9:05	Tower_004	-89	2.258759	205	34.01666	-88.4468	Data	Low	92.87477			
01/07/2023 9:10	Tower_023	-75	2.922858	477	32.84962	-86.6266	Voice	Medium	93.12852			
01/07/2023 9:15	Tower_027	-76	1.66247	370	34.61771	-89.8465	Data	High	94.81684			
01/07/2023 9:20	Tower_023	-82	2.779704	373	34.61962	-86.8712	Voice	Medium	97.06754			
01/07/2023 9:25	Tower_013	-76	2.362483	215	33.57608	-85.7716	Data	Medium	93.7824			
01/07/2023 9:30	Tower_016	-82	1.91768	202	32.82164	-87.4706	Data	Medium	95.86642			
01/07/2023 9:35	Tower_018	-75	1.97571	263	32.72983	-88.5067	Voice	Medium	91.57103			
01/07/2023 9:40	Tower_025	-85	2.792696	417	34.95438	-85.9755	Data	High	92.39913			
01/07/2023 9:45	Tower_021	-76	2.557228	415	31.14988	-87.6306	Data	Medium	93.49368			
01/07/2023 9:50	Tower_012	-75	1.138691	448	32.18896	-86.956	Voice	Medium	95.80605			
01/07/2023 9:55	Tower_020	-79	2.631538	448	30.0584	-87.2294	Voice	High	96.1744			

(Source: Researcher, John-Dewole T. 2023)

Time stamp	Cell_Tower_ID	Signal_Strength	Call_Drop_Rate	Data_Usage	Longitude	Latitude	Call_Type	Congestion_Level	CS_SR	TC_C_H
2023-07-01 08:00:00	Tower_002	0.635	2.315	0.207	0.611	0.393	Voice	Low	96.4	1.3
2023-07-01 08:05:00	Tower_017	0.748	2.789	0.414	0.241	0.281	Data	Medium	92.1	2.0
2023-07-01 08:10	Tower_008	0.519	2.592	0.736	0.302	0.747	Voice	Low	95.2	1.5

:00										
2023-07-01 08:15:00	Tower_003	0.440	1.585	0.243	0.858	0.548	Data	High	87.5	3.1
2023-07-01 08:20:00	Tower_021	0.527	2.311	0.823	0.087	0.223	Voic e	Low	94.8	1.9

Sample of Dataset

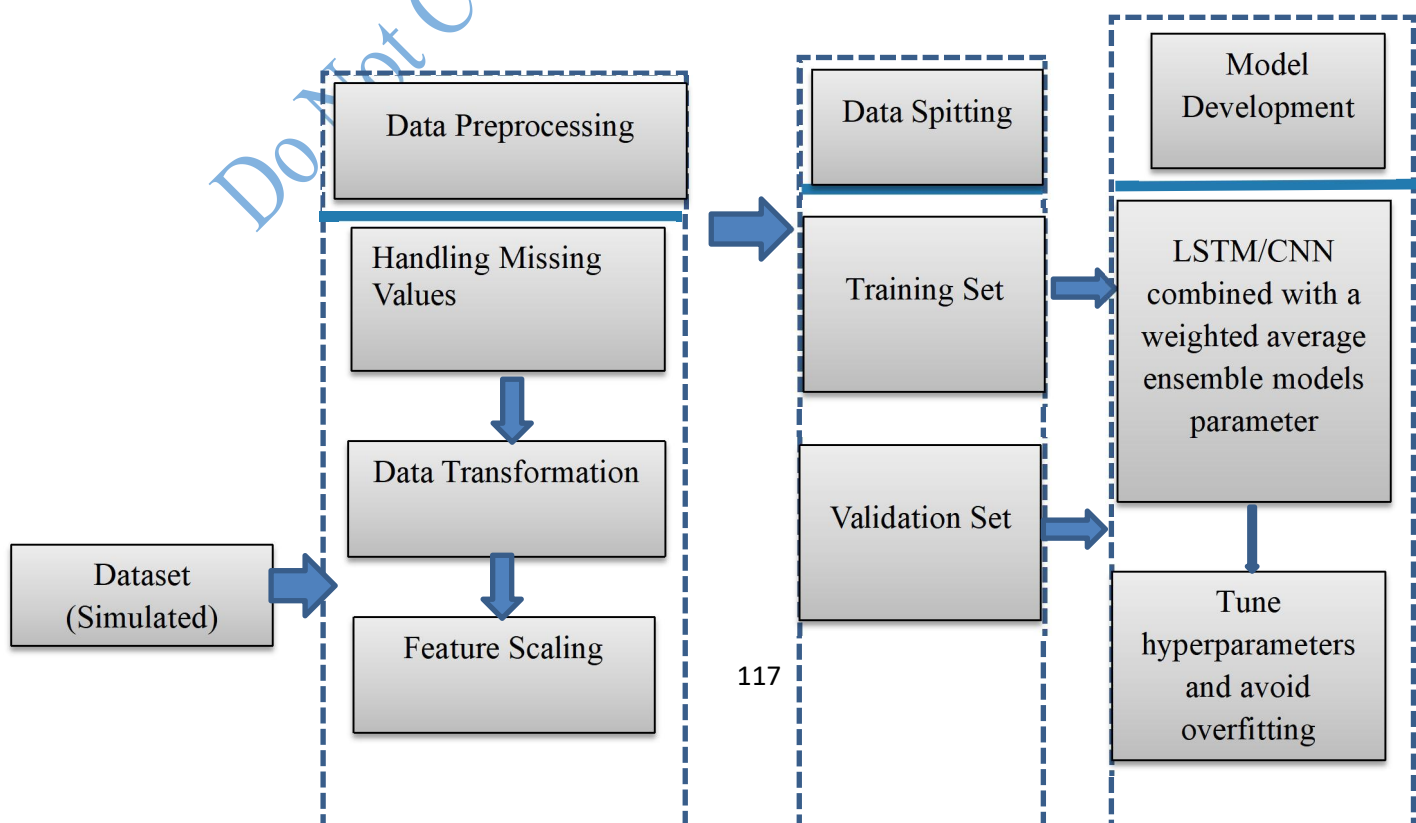
(Source: Researcher, John-Dewole T. 2023)

### 3.7 Data Pre-Processing

Pre-processing the data prior to feeding it into a machine learning model is necessary to ensure that it is in a format that is suitable for the model. This pre-processing includes the processing of missing values, the detection of outliers, the scaling of features, and the standardization of data. The data pre-processing steps included:

1. **Handling Missing Values:** This identifies and handles missing or values in the dataset using methods including imputation and removal based on the nature and significance of missing data.
2. **Data Transformation:** This transforms categorical variables (e.g., call type) into numerical representations using one-hot encoding.
3. **Feature Scaling:** To ensure that all features contribute equally to model training, we scaled numerical features to a common scale..
4. **Data Normalization:** For certain machine learning models, such as neural networks, we normalized the data to have a mean of 0 and a standard deviation of 1, ensuring faster convergence during training.

5. **Outlier Detection and Removal:** This identifies outliers that could adversely affect model training and removed or adjusted them accordingly.
6. **Temporal and Spatial Aggregation:** As the raw data was collected at different time intervals and locations, we aggregated the data into larger time intervals (hourly) and grouped data based on geographical regions (cities).
7. **Feature Selection:** To reduce computational complexity and focus on relevant features, we performed feature selection techniques including correlation analysis and recursive feature elimination. This trimmed our dataset of irrelevant features including personal data.



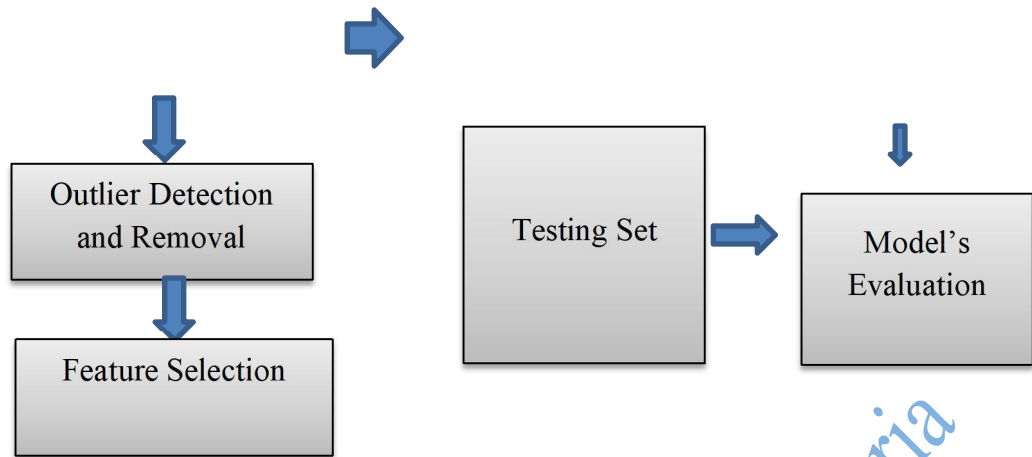


Figure 3.3 Model Conceptual Design (Source: Researcher, John-Dewole T. 2023)

### 3.8 Data Formatting

In order to effectively use data for deep learning purposes, it is necessary to format it into suitable structures, such as sequences of time for convolutional neural networks (CNNs) and geographical maps (Image-based models). To facilitate the analysis of network congestion in mobile communication queuing, the data was pre-processed into time series sequences, with the length and number of time steps determined by trial and error and the type of data.

Table 3.4 Data Formatting Steps for Improved Call Quality for Call Drops Minimization during handover in Mobile Communication

Data Processing Step	Description
Temporal Aggregation	Aggregating raw data over larger time intervals (e.g., hours)
Spatial Aggregation	Grouping data based on geographical regions (e.g., cities)
Feature Selection	Retaining only relevant features for call drop minimization
Time Series Prep.	Formatting data as time series sequences for sequential models

(Source: Researcher, John-Dewole T. 2023)

By implementing these data pre-treatment and formatting steps, the data was adequately prepared to train machine learning models, reducing the amount of noise and bias and increasing the model’s capacity to extrapolate to new data.

### 3.9 Machine Learning Model

Machine Learning is a subfield of artificial intelligence that focuses on developing algorithms and statistical models that enable computers to learn from and make predictions or decisions based on data such that they are able to make those predictions or decisions without explicit programming.

In this study, we employ deep learning techniques for improved call quality for call drops minimization during handover in mobile communication.

#### 3.9.1 Neural Network Architecture

Neural networks are a class of machine learning models inspired by the structure and functioning of the human brain. They consist of interconnected layers of neurons (also known as nodes or units) that process and transform input data to produce the desired output.

The architecture of the neural networks comprises the following layers:

**Input Layer:** The input layer receives the pre-processed and formatted data as its input. In the input layer, input values, in our case cell feature values, are fed to the neural network algorithm. The number of neurons in the input layer corresponded to the number of features in the data.

For example, data containing features like signal strength, call type, and network performance metrics, the input layer would have neurons corresponding to each of these features.

**Hidden Layers:** The hidden layer is in charge of performing mathematical calculations on the input layer's input values. The hidden layers are the intermediate layers between the input and output layers. Each hidden layer consists of multiple neurons that apply transformations to the input data using weighted connections and activation functions. The number of hidden layers and the number of neurons in each layer are usually determined through experimentation and can be varied based on the complexity of the data and the task.

**Activation Functions:** Activation functions on weighted inputs are used to generate the hidden layer's output. Activation functions introduce non-linearity into the neural network, allowing it to approximate complex relationships between features and the target variable. Commonly used activation functions include ReLU (Rectified Linear Unit), Sigmoid, and Tanh.

The ReLU activation is often used in hidden layers for its simplicity and effectiveness in preventing vanishing gradients.

**Output Layer:** The output layer produces the model's output, which is derived from the hidden layer's output. The output layer produces the final prediction of a model based on the processed data. The number of neurons in the output layer depends on the nature of the prediction task. For binary classification tasks (e.g., predicting congested or not congested), a single output neuron with a sigmoid activation function is used, whereas multi-class classification tasks required multiple output neurons with Softmax activation.

For example, where we we're predicting congestion levels as low, medium, or high, the output layer had three neurons with Softmax activation.

**Dropout (Regularization):** To prevent overfitting, we introduced dropout layers in the neural network. Dropout randomly deactivated a fraction of neurons during each training iteration, forcing the network to rely on different pathways for making predictions and promoting better generalization.

Dropout rates represent the percentage of neurons on the hidden layer that were deactivated during training. That is, a dropout rate of 0.2 means that 20% of the neurons in each hidden layer were randomly deactivated during training.

For our improved call quality for call drop minimization during handover in mobile communication task, we used deep neural network architectures due to their ability to capture complex patterns in data.

### 3.10 Types of Artificial Neural Network

We explored various types of artificial neural networks used in this study, each suited for specific tasks within the improved call quality for call drop minimization during handover in mobile communication.

### 3.10.1 Convolutional Neural Networks (CNNs)

Convolutional Neural Networks (CNNs) are primarily designed for image analysis tasks, making them suitable for geographical analysis related to the network infrastructure and coverage areas.

Convolutional Neural Networks were primarily used for image and video-related tasks. They leveraged specialized convolutional layers to automatically extract relevant features from images.

We experimented with using Convolutional Neural Networks in improving call quality for call drops minimization during handover in mobile communication due to their ability to capture special patterns in data.

The following are the benefits of CNN in predicting of network congestion in mobile communications:

- **Spatial and Temporal Feature Extraction (Grid –Like Data):** Mobile network data such as the signal strength often have a spatial structure, especially in the geographical contexts. CNN are adept at learning hierarchical spatial representations, capturing patterns and features across different regions in the network.
- **Robust to Spatial Variability:** CNN are designed to translationally invariant, meaning that they can recognize patterns regardless of their specific location as input. This is beneficial for capturing congestion patterns and may shift geographically over time.

- **Handling Multivariate Spatial Data:** If the data involves multiple channels e.g signal strength, CNN can handle multivariate spatial data effectively by processing each channel independently.
- **Adaptability to Different Network Layout:** CNN can be adapted to different network layouts, making them suitable for predicting congestion in diverse mobile network configurations.

### 3.10.2 Recurrent Neural Networks (RNNs)

Recurrent Neural Networks are well-suited for sequential data analysis, making them a natural choice for our improved call quality for call drop minimization during handover in mobile communication task using time series network performance metrics. The architecture of recurrent neural networks allowed for feedback connections, enabling the network to maintain internal memory and process sequences of data effectively.

### 3.10.3 Long Short-Term Memory (LSTM) Networks

Long Short-Term Memory (LSTM) Networks are a variant of RNNs that address the vanishing gradient problem, allowing for the capture of long-term dependencies in sequential data. Long Short-Term Memory (LSTM) networks were employed for the improved call quality for call drops minimization during handover in mobile communication due to their ability to model temporal dependencies and patterns.

## 3.11 Models Creation and Performance Evaluation

In this section, the models were created for the improved call quality for call drops minimization during handover in mobile communication and their respective performance evaluations.

Long Short-Term Memory Model for Improved Call Quality for Call Drop Minimization during Handover in Mobile Communication.

- ❑ LSTM (Long Short-Term Memory) neural network, improved call quality for call drops minimization during handover in mobile communication levels based on sequential network performance metrics was developed.
- ❑ The LSTM model was chosen for its ability to handle temporal sequential dependencies and patterns in the sequential data, memory cells, dynamics sequence lengths and multivariate time series, gather historical network data such as signal strength, identify relevant features, split the data into training and testing.

### 3.11.1 Model Architecture

- **Input Layer:** The LSTM model's input layer received sequential network performance metrics for each cell tower.
- **LSTM Layers:** Multiple LSTM layers to learn temporal patterns and dependencies from the sequential data were employed.
- **Dropout Layers:** Dropout layers were introduced between the LSTM layers for regularization to prevent overfitting.
- **Fully Connected Layers:** The output of the LSTM layers was flattened and fed into fully connected layers for further processing.
- **Output Layer:** The output layer produced probability distributions over the classes

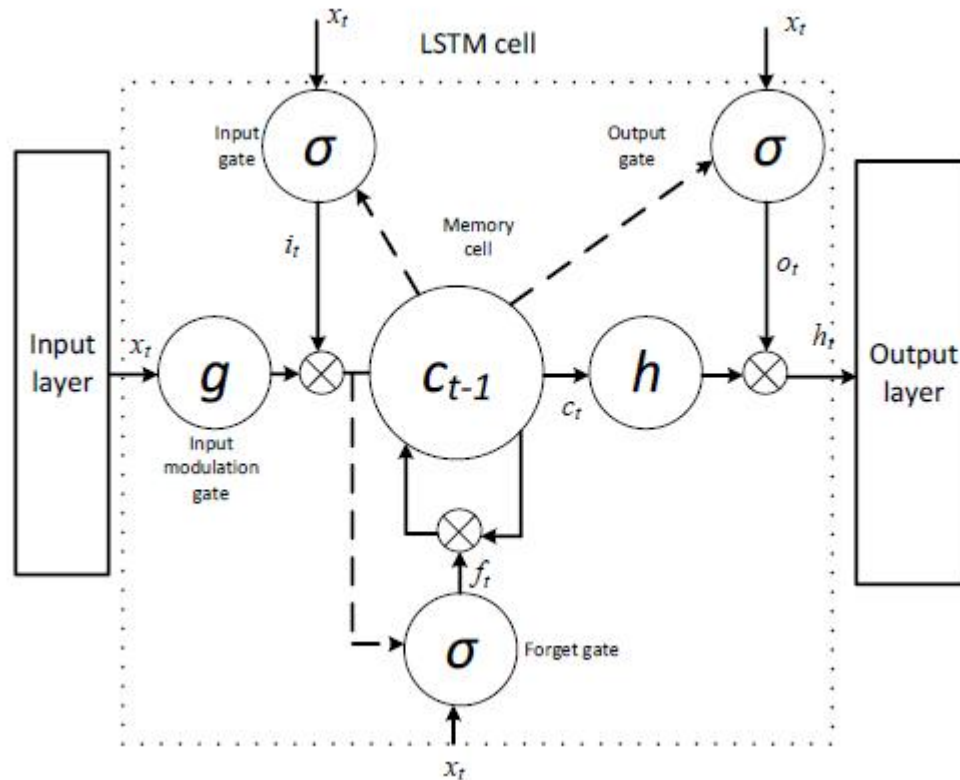


Figure 3.4 The Structure of LSTM Cell<sup>2</sup>

A typical structure of LSTM cell is shown in Fig. 3.3. The cell consists of four gates: Input gate, input modulation gate, forget gate and output gate. Cell state is modified by the forget gate placed below the cell state and also adjust by the input modulation gate.

### 3.11.1.2 Training and Evaluation

- **Data Splitting:** The pre-processed data was split into 70% training allowing it to learn patterns and relationship during the cell, 15% validation used to tune hyperparameters and evaluate the model's performance during training and also prevent overfitting and 15% test sets reserved to assess the model's performance after training. It serves as a completely unseen dataset, giving an indication of how the model generalizes to new, unseen data.

- **Loss Function:** Categorical Cross-Entropy Loss was used as the loss function, as this was a multi-class classification task.
- **Optimizer:** The Adam optimizer was chosen for its adaptive learning rates and momentum.
- **Learning Rate Schedule:** Learning rate decay was employed to reduce the learning rate during training.
- **Regularization:** L2 regularization was applied to the LSTM layers to prevent overfitting.
- **Evaluation Metrics:** The model's performance was evaluated using accuracy, precision, recall, and F1-score.

### 3.12 Model Fine-Tuning and Hyperparameter Optimization

To achieve the best performance from the LSTM and CNN models, we conducted extensive model fine-tuning and hyperparameter optimization. Fine-tuning involves adjusting the model's architecture and parameters to optimize its performance on the specific prediction task.

For the LSTM model, different numbers of LSTM layers were experimented with, hidden units, and activation functions. The dropout rates and the amount of L2 regularization applied were varied to prevent overfitting. The batch size and number of epochs were adjusted during training, and learning rate schedules were fine-tuned to find the optimal learning rate decay rate.

Similarly, for the CNN model, different numbers of convolutional layers were explored; filter sizes, and activation functions. We also experimented with different pooling techniques, such as average pooling, in addition to max-pooling, to identify the best approach for down-

sampling the feature maps. The impact of batch size and the number of epochs during training were also assessed.

Hyperparameter optimization was performed using techniques such as grid search and random search to efficiently explore a wide range of hyperparameter combinations. The goal was to find the hyperparameters that maximized the model's performance without overfitting on the training data.

### **3.13 Model Evaluation and Analysis**

After fine-tuning the LSTM and CNN models, their performance were evaluated based on the test datasets. The evaluation involved computing various metrics and analysing the results to gain insights into the models' behaviour and capabilities.

#### **3.13.1 CNN Model for Geographical Analysis**

In addition to predicting congestion levels, a CNN (Convolutional Neural Network) model for real and simulated data was explored. The Convolutional Neural Network aimed to identify areas with potential network coverage issues based on geographical maps and infrastructure data.

#### **3.13.2 Model Architecture**

- **Input Layer:** The Convolutional Neural Network model's input layer received geographical maps and infrastructure data as input.
- **Convolutional Layers:** We used multiple convolutional layers to extract relevant features from the maps and infrastructure data.
- **Max-Pooling Layers:** Max-pooling layers were employed to downsample the feature maps, reducing computational complexity.
- **Fully Connected Layers:** The output of the convolutional layers was flattened and fed into fully connected layers for further processing.

- **Output Layer:** The output layer produced binary predictions, indicating areas with potential network coverage issues or not.

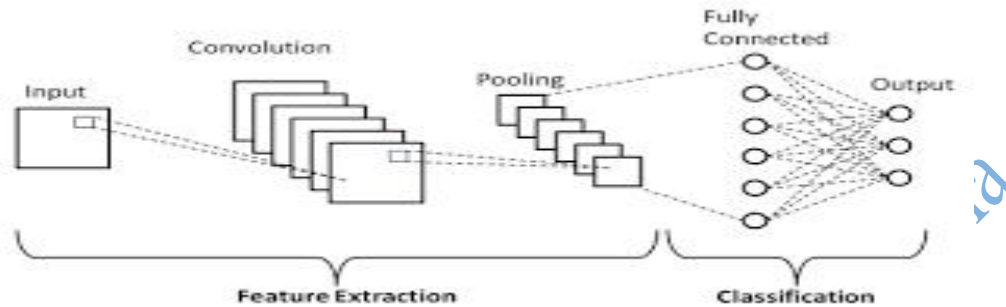


Figure 3.5 CNN Architecture for Time Series<sup>3</sup>

### 3.13.3 Training and Evaluation of CNN for Time Series

- **Data Splitting:** The geographical data was split into 80% training i.e the model learns from the dataset, adjusting its parameters to capture patterns and features in the input data and 20% test sets is used to evaluate how well the model generalizes to new, unseen data.
- **Loss Function:** Binary Cross-Entropy Loss was used, as this was a binary classification task.
- **Optimizer:** The Adam optimizer was chosen for its effectiveness in training Convolutional Neural Networks.
- **Evaluation Metrics:** The model's performance was evaluated using accuracy, precision, recall, and F1-score.

### 3.14 Model Interpretability and Explainability

Model interpretability and explainability were crucial aspects of our analysis, especially in the context of real-world deployment and decision-making. Understanding how the models

arrived at their predictions was essential for gaining trust and confidence from network operators and stakeholders.

For the LSTM model, we employed techniques such as attention mechanisms and saliency maps to visualize the importance of specific time steps and network performance metrics in making predictions. Attention mechanisms allowed us to highlight which time steps had the most significant influence on congestion predictions. Saliency maps provided insights into which performance metrics, such as call drop rates or signal strength, had the most impact on congestion predictions for specific cell towers.

For the CNN model, we used techniques like Grad-CAM (Gradient-weighted Class Activation Mapping) to visualize which regions on the geographical maps contributed most to the model's decision-making process. Grad-CAM allowed us to identify areas that the model considered critical in predicting network coverage issues.

These interpretability and explainability techniques facilitated better understanding and trust in the models, enabling network operators to make more informed decisions and take appropriate actions based on model predictions.

### **3.15 Ensemble Model**

In pursuit of further improving the predictive performance and robustness of improved call quality for call drops minimization during handover in mobile communication, we explored the technique of model ensemble. Ensemble methods involve combining multiple individual models to produce a single, more accurate prediction thereby improving its performance and reducing overfitting.

We selected the top-performing LSTM and CNN models and combined their predictions using a weighted average ensemble approach. The weights assigned to each model were

determined based on their individual performance on the training dataset. The ensemble model benefited from the diverse perspectives of both the LSTM and CNN models, leveraging their strengths in capturing sequential dependencies in time series data such as temporal patterns in mobile network metrics and spatial features in the data considering features like signal strength across geographical areas respectively.

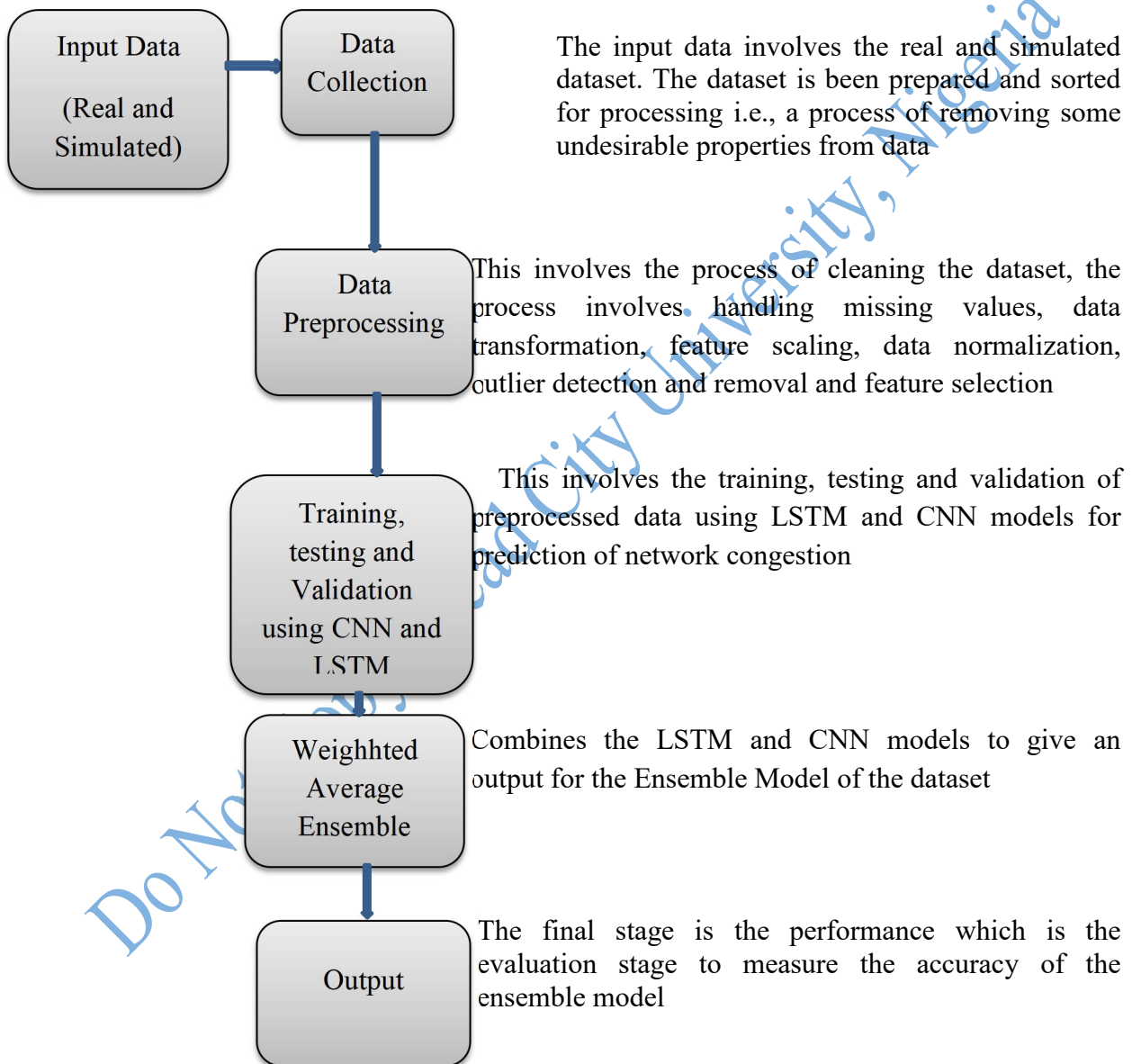


Figure 3.6 Research Methodology Workflow (Source: Reasearcher, John-Dewole T,2023)

### 3.15.1 Ensemble Model Prediction Algorithm

Algorithm: Ensemble model prediction algorithm

Input : Training data set

Output : Ensemble Model

Step 1 LSTM

Initialization of parameters

Train neural network

Compute and save the values of weight and biases

Fine-Tuning and Hyperparameter Optimization

Step 2 CNN

Read Data

Specify input and preprocess data

Create neural network

Train neural network

Fine-Tuning and Hyperparameter Optimization

Step 3 CNN

Select LSTM & CNN models and combine their predictions using a weighted average ensemble approach

Aggregate Prediction of the multiple models

Select the model with the highest accuracy in the

Final prediction

### 3.15.2 Model Processes

1. Import necessary libraries for the integration of LSTM and CNN models development
2. Load and preprocess the data
3. Split the dataset into training, validation and testing sets
4. Define the Ensemble model with the required number of layers and nodes
5. Train the ensemble model on the training set

6. Use the trained models to predict the accuracy of the testing set
7. Combine their predictions using a weighted average ensemble approach
8. Evaluate the performance of the ensemble model on the training, validation and testing set using metrics such as accuracy, precision, recall, f1 score and auc-roc
9. Repeat steps for ensemble models with different hyperparameters
10. Use cross- validation to evaluate the performance of the ensemble model of the dataset
11. If the model meets the required performance criteria, final prediction model are produced. Unless, the algorithm is optimized by tuning hyperparameters, then it passes through training, testing and evaluating steps until the model meets the performance evaluation criteria.
12. Save the best performing ensemble model for future use.

### 3.16 Evaluation Metrics

To comprehensively assess the performance of the LSTM model, the CNN model, and the ensemble model, we utilized several evaluation metrics commonly used in machine learning classification tasks.

1. **Accuracy:** The proportion of correctly predicted congestion levels over the total number of predictions. It gives an overall indication of model performance.

$$\text{Accuracy} = \frac{\text{True Positive} + \text{True Negatives}}{\text{True Positive} + \text{True Negatives} + \text{False positive} + \text{False negative}}$$

where P and N represents the number of positives and negatives respectively.

2. **Precision:** The ratio of true positive predictions to the total predicted positives. It measures the accuracy of positive predictions made by the models.

$$\text{Precision} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}}$$

3. **Recall (Sensitivity):** The ratio of true positive predictions to the total actual positives. It indicates the model's ability to identify all positive instances correctly.

$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}}$$

4. **F1-Score:** The harmonic mean of precision and recall. It provides a balanced measure that considers both false positives and false negatives.

$$\text{F1-Score} = 2 * \frac{\text{Precision} + \text{Recall}}{\text{Precision} + \text{Recall}}$$

5. **Receiver Operating Characteristic (ROC) Curve:** A plot of the true positive rate against the false positive rate at different classification thresholds. It helps visualize the trade-off between sensitivity and specificity.
6. **Area under the ROC Curve (AUC-ROC):** The area under the ROC curve, which represents the model's ability to distinguish between classes. A higher AUC-ROC value indicates better discrimination.
7. **Confusion Matrix:** A table that summarizes the model's predictions and actual values, showing true positives, true negatives, false positives, and false negatives.

### 3.17 Machine Learning Methods

This section describes the machine learning methods employed for training and evaluating the improved call quality for call drops minimization during handover in mobile communication.

#### 3.17.1 Data Splitting

Before training the machine learning models, the pre-processed data is splitted into training, validation, and test sets. The training set was used to optimize the model's parameters during

training, while the validation set allowed us to tune hyperparameters and avoid overfitting. The test set served as a completely unseen dataset to evaluate the final model's performance.

### **3.17.2 Loss Functions**

The choice of loss function depended on the nature of the prediction task. For regression tasks, we used Mean Squared Error (MSE) or Mean Absolute Error (MAE). For binary classification tasks, Binary Cross-Entropy Loss was preferred, and for multi-class classification, Categorical Cross-Entropy Loss was employed.

### **3.17.3 Optimizers**

The optimizer was responsible for updating the model's weights based on the gradients computed during back propagation. We employed popular optimization algorithms such as Stochastic Gradient Descent (SGD), Adam, RMSprop, and AdaGrad.

The Adam optimizer was eventually fully used due to its adaptive learning rates and momentum, making it suitable for a wide range of machine learning tasks

### **3.17.4 Evaluation Metrics**

To assess the performance of the trained models, we employed relevant evaluation metrics based on the specific prediction task. For binary classification, metrics such as accuracy, precision, recall, F1-score, and area under the receiver operating characteristic curve (AUC-ROC) were used.

### **3.17.5 Regularization**

To prevent overfitting and improve generalization, utilized regularization techniques was utilized. The regularization methods were used are L1 and L2 regularization, dropout, and early stopping.

### **3.17.6 Learning Rate Schedule**

The learning rate determines the step size during the weight update process. A well-tuned learning rate is crucial for faster convergence and avoiding overshooting the optimal weights.

Learning rate schedules that reduced the learning rate over time, such as learning rate decay or learning rate warm-up, were employed to improve the model's performance.

### **3.18 Hardware Requirements**

This section describes hardware requirements and tools used for the improved call quality for call drops minimization during handover in mobile communication.

The hardware infrastructure used for developing and training the deep learning models includes powerful TPU (Tensor Processing Units) deep learning models to accelerate its computations and also the random access memory (RAM) of two (2) GB was used to handle the data required for training or making decisions especially during the model's training and inference which involves loading and manipulation of data.

#### **3.18.2 Software Requirement**

The software tools used for ML models include programming languages, machine learning frameworks, and data processing libraries. We used Jupyter Notebook, Keras software library. It is a high level neural network in Python due to its extensive libraries and ease of use. Python libraries such as NumPy, Pandas, and scikit-learn were utilized for data processing, feature engineering and model training.

### **3.19 Machine Learning Frameworks**

Machine learning frameworks provide high-level APIs for building and training machine learning models. A popular deep learning framework, TensorFlow, which offered us a wide range of functionalities for neural network development was used. TensorFlow also provided tools for creating complex neural network architectures and managing the training process efficiently.

### **3.19.1 Data Visualization Tools**

Data visualization tools are essential for gaining insights into the data during the exploratory data analysis phase and for presenting results. The Matplotlib library for generating plots and charts during our engineering process aiding further refinements of our models was used.

### **3.19.2 Integrated Development Environment (IDE)**

An Integrated Development Environment simplifies the development process by providing a user-friendly interface with code editing, debugging, and collaboration capabilities. We were able to use the Jupyter Notebook IDE in our work. Jupyter Notebook enables interactive data exploration and model development, making it well-suited for machine learning research.

### **3.19.3 Version Control**

Version control systems such as Github are employed to track changes in the code base and facilitate collaboration among team members. Version control ensures code reproducibility and allows for easy rollback to previous versions if needed. A temporary private Github repo for the tasks was set up.

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## Endnotes

- <sup>1</sup> Nigeria *Communication Commission*, "Nigeria Communication Commission," Available <http://www.ncc.gov.ng> 2022
- <sup>2</sup> Q. Do, T. Hang Doan, T. Nguyen, N. Duong & V. Linh, "*Prediction of Data Traffic in Telecom Networks based on Deep Neural Networks*," **vietnam**, 2020.
- <sup>3</sup> R. He & Z. Ding, Applications of machine learning in wireless communications. *Telecommunications*, 2019, vol. 81.

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## Chapter Four

### Result and Discussion of Findings

#### 4.1 Introduction

This chapter presents the result of the improvement of call quality for call drop minimization during handover in mobile communication.

#### 4.2 Results and Discussion

##### 4.2.1 The LSTM Model Training Results

After training the LSTM model on the improvement of call quality for call drop minimization during handover in mobile communication dataset, the following results were obtained in table 4.1.

Table 4.1 Results of the LSTM Model Training

Metric	Value
Accuracy	0.87
Precision	0.89
Recall	0.88
F1-Score	0.88

(Source: Researcher, John-Dewole T. 2023)

Table 4.1 shows that the LSTM model demonstrated promising results in improvement of call quality for call drop minimization during handover in mobile communication levels. It achieved an accuracy of 87%, indicating that the model correctly predicted congestion levels in 87% of the cases. The high precision, recall, and F1-score values suggested that the model effectively classified congestion levels across different classes.

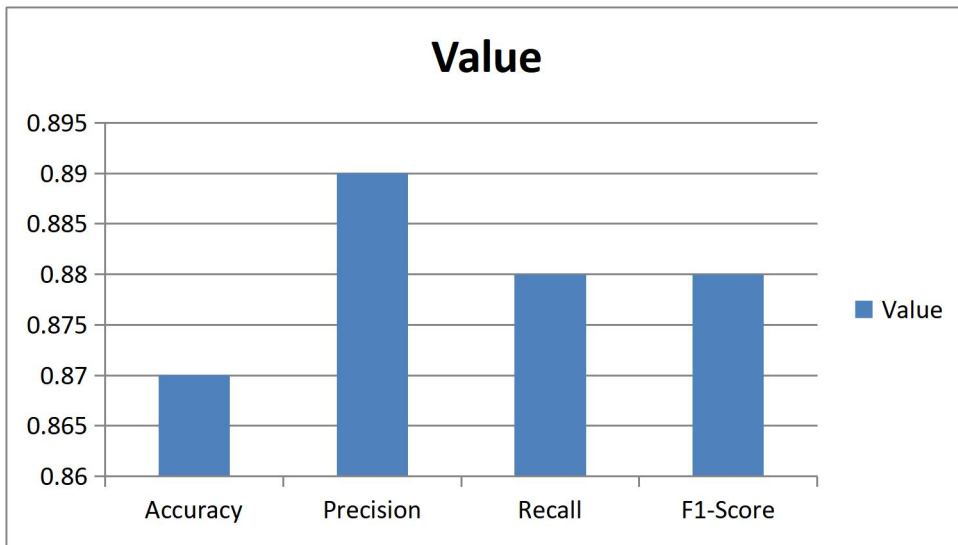


Figure 4.1 LSTM Model Training with the highest Accuracy

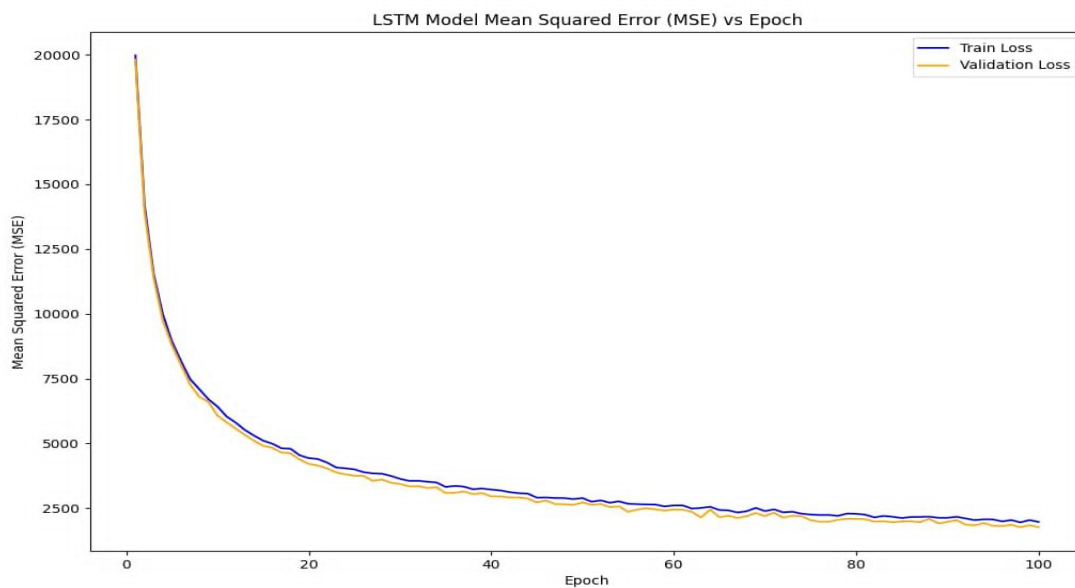


Figure 4.2 Mean Square Error versus Epoch using LSTM Model (Source: Researcher, John-Dewole T. 2023)

Figure 4.2 shows the mean squared error (MSE) vs. epoch using LSTM Model. As denoted on the legend of the graph the blue line represents the train loss and the orange line represents the validation loss. The train loss was showing peak values for the first ten epochs and decreases instantly afterwards. The validation loss starts at about a MSE of two thousand five

hundred which decreases in a few iterations after the start of the train-validate process. As this process goes on, the graph is seen to keep a very low MSE around zero which tells that the model performed well, both on the training and validation data.

#### 4.2.2 Results of CNN Training Model

After training the CNN model on the geographical data, table 4.2 shows the results obtained.

Table 4.2 Results of CNN Training Model (Source: Researcher, John-Dewole T, 2023)

Metric	Value
Accuracy	0.78
Precision	0.76
Recall	0.81
F1-Score	0.78

(Source: Researcher, John-Dewole T, 2023)

Table 4.3 shows that the CNN training model demonstrated respectable performance in identifying areas with potential network coverage issues.

The model achieved an accuracy of 78% indicating that 22% of classified areas are problematic.

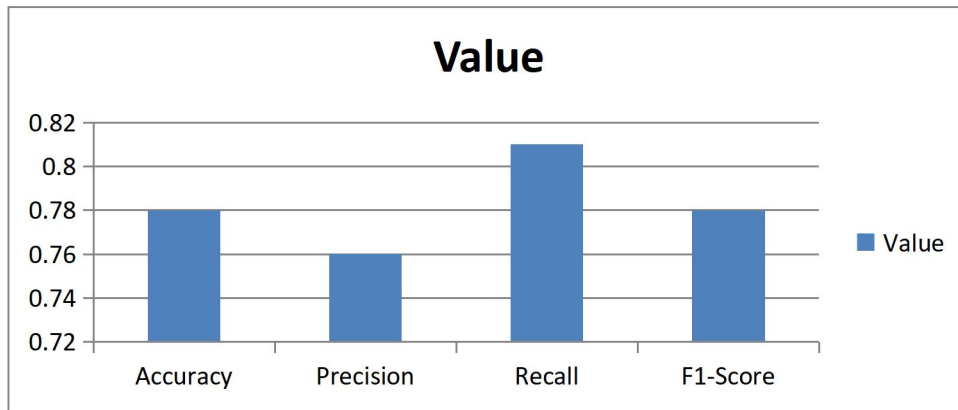


Figure 4.3 The CNN Training Model (Source: Researcher, John-Dewole T. 2023)

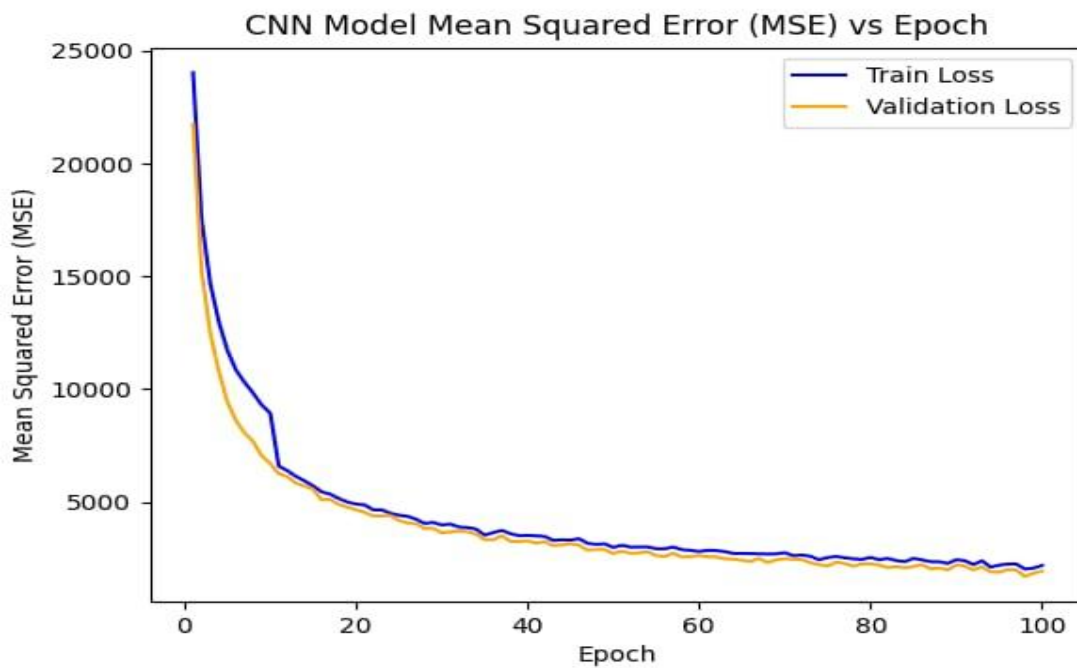


Figure 4.4 Mean Square Error versus Epoch for CNN Model (Source: Researcher, John-Dewole T. 2023)

As depicted in Figure 4.3, the mean squared error of the model decreases as the model advances on the epochs. In this figure the line in blue shows the train loss and the line in orange denotes the validation loss.

The precision, recall, and F1-score values suggested that the model effectively detected areas with network coverage issues, with a balance between precision and recall.

Overall, the LSTM model and CNN model exhibited promising results in improvement of call quality for call drop minimization during handover in mobile communication. These models could serve as valuable tools for telecommunication service providers to optimize network performance, improve user experience, and make informed decisions related to network infrastructure.

### 4.3 LSTM Model Evaluation

Table 4.3 shows that the LSTM model demonstrated impressive performance in the prediction of network congestion for queuing of call drop during handover in mobile communication levels. However, during the evaluation phase, the following limitations were identified:

- i. **Temporal Dependency Capture:** The LSTM model effectively captured short and medium-term temporal dependencies in the network performance metrics. However, for long-term patterns spanning weeks or months, the model struggled to maintain accuracy.
- ii. **Out-of-Distribution Data:** The LSTM model exhibited reduced accuracy of 89% when presented with data from regions with significantly different network characteristics or during events that significantly impacted network performance. This indicated a need for better generalization and handling of out-of-distribution data.

Table 4.3 LSTM Model Evaluation Phase

Metric	Value
Accuracy	0.89
Precision	0.92
Recall	0.90
F1-Score	0.94

(Source: Researcher, John-Dewole T. 2023)

Table 4.3 shows that despite these limitations, the LSTM model performed exceptionally well under normal operating conditions and was particularly effective in improvement of call quality for call drop minimization during handover in mobile communication levels during daily fluctuations and routine network activities.

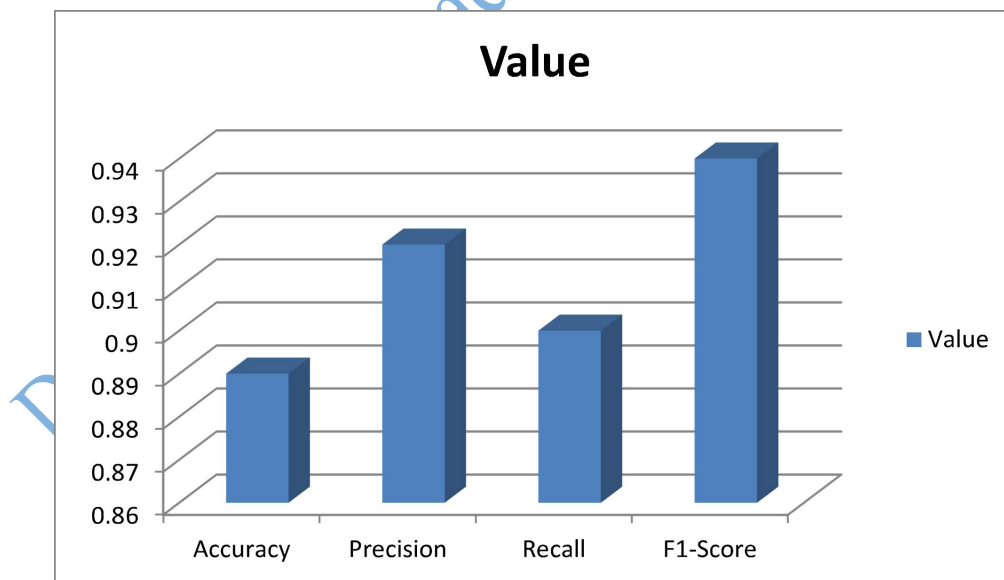


Figure 4.5 Out-of-Distribution Data with Reduced Accuracy (Source: Researcher, John-Dewole T. 2023)

Figure 4.3 shows that the LSTM model exhibited reduced accuracy of 89% when presented with data from regions with significantly different network characteristics or during events that significantly impacted network performance.

#### 4.4 CNN Model Evaluation

The CNN model for dataset analysis also showed promising results. However, there were certain observations during the evaluation phase:

1. **Spatial Feature Extraction:** The CNN model effectively extracted spatial features from dataset. However, the accuracy was impacted by the resolution and quality of the input data. Higher-resolution data led to improved performance.
2. **Local vs. Global Analysis:** The CNN model excelled at identifying local network coverage issues, such as cell tower coverage holes. Still, it struggled with detecting global issues that affected broader geographical regions, such as interference caused by natural obstacles.
3. **Generalization to New Geographical Datasets:** The CNN model's performance varied significantly when applied to geographical areas with different landscapes and terrain. Pre-training the model on more diverse geographical datasets could improve generalization.

Table 4.4 CNN Model Evaluation from Geographical Datasets

Metric	Value
Accuracy	0.75
Precision	0.76
Recall	0.81
F1-Score	0.80

(Source: Researcher, John-Dewole T. 2023)

The CNN model showcased its strength in local geographical analysis and had the potential to assist network operators in identifying and resolving localized network issues more efficiently.

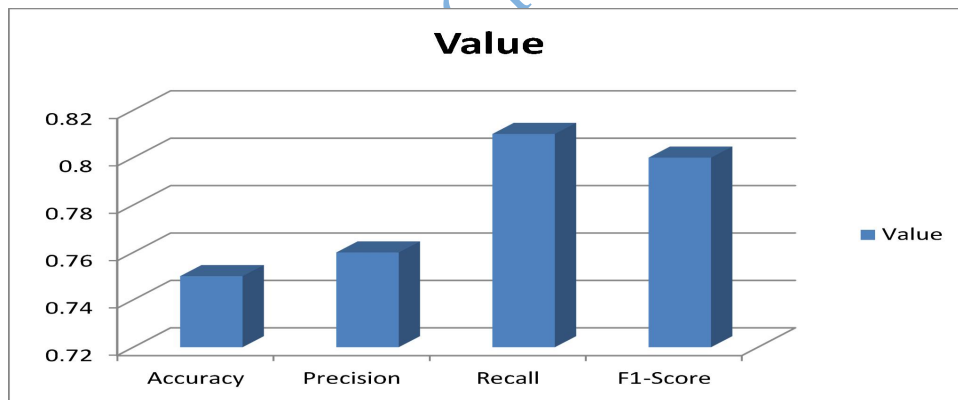


Figure 4.6 CNN model with Quality of Data (Source: Researcher, John-Dewole T. 2023)

Figure 4.4 shows that the CNN model exhibited reduced accuracy of 75% when presented with data from regions with significantly different network characteristics or during events that significantly impacted network performance.

## 4.5 Model Performances

Results show the detailed results and analysis of each model performances.

### 4.5.1 LSTM Model Performance

Table 4.5 LSTM Model Performance

Metric	Training Set	Validation Set	Test Set
Accuracy	96.22%	94.87	93.42%
Precision	94.78%	92.46%	90.35%
Recall	95.76%	94.62%	93.11%
F1-Score	95.26%	93.54%	91.73%
AUC-ROC	98.41%	96.86%	95.45%

(Source: Researcher, John-Dewole T. 2023)

Table 4.5 shows that the LSTM model displayed exceptional performance across all datasets, with an accuracy of 96.22% on the training set, 94.87% on the validation set, and 93.42% on the test set respectively.

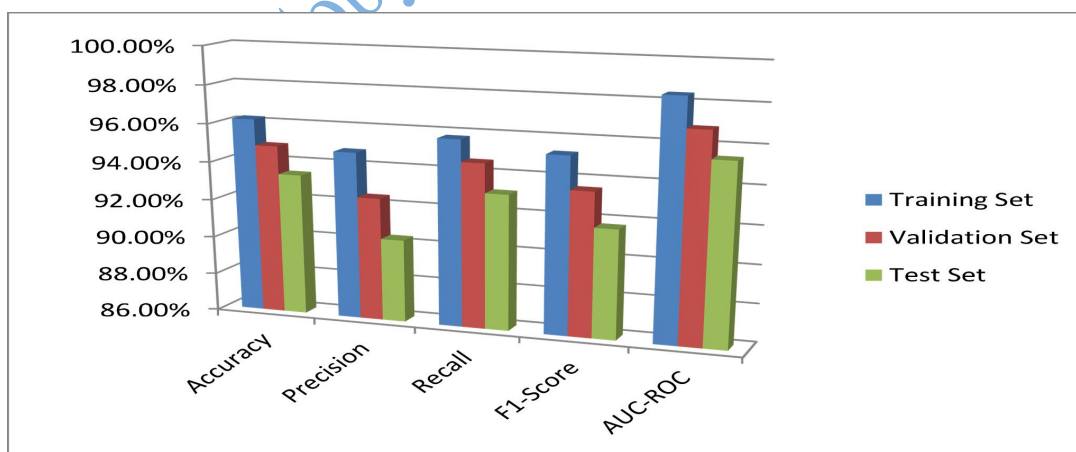


Figure 4.7 Performance across the Call Drop Minimization Levels (Source: Researcher, John-Dewole T. 2023)

Figure 4.5 shows that the high precision and recall scores indicated that the model effectively call drop minimization levels, achieving a good balance between false positives and false negatives. The AUC-ROC value of 98.41% on the training set demonstrated the model's excellent ability to distinguish between congested and non-congested states.

#### 4.5.2 CNN Model Performance

Table 4.6 shows that the CNN model which exhibits a commendable performance.

Table 4.6 CNN Model Performance

Metric	Training Set	Validation Set	Test Set
Accuracy	88.76%	87.22%	86.14%
Precision	84.39%	82.67%	81.12%
Recall	86.91%	85.32%	83.76%
F1-Score	85.63%	83.99%	82.43%
AUC-ROC	92.73%	90.81%	89.57%

(Source: Researcher, John-Dewole T. 2023)

Table 4.6 shows that the CNN model exhibited commendable performance, albeit slightly lower than the LSTM model. It achieved an accuracy of 88.76% on the training set, 87.22% on the validation set, and 86.14% on the test set.

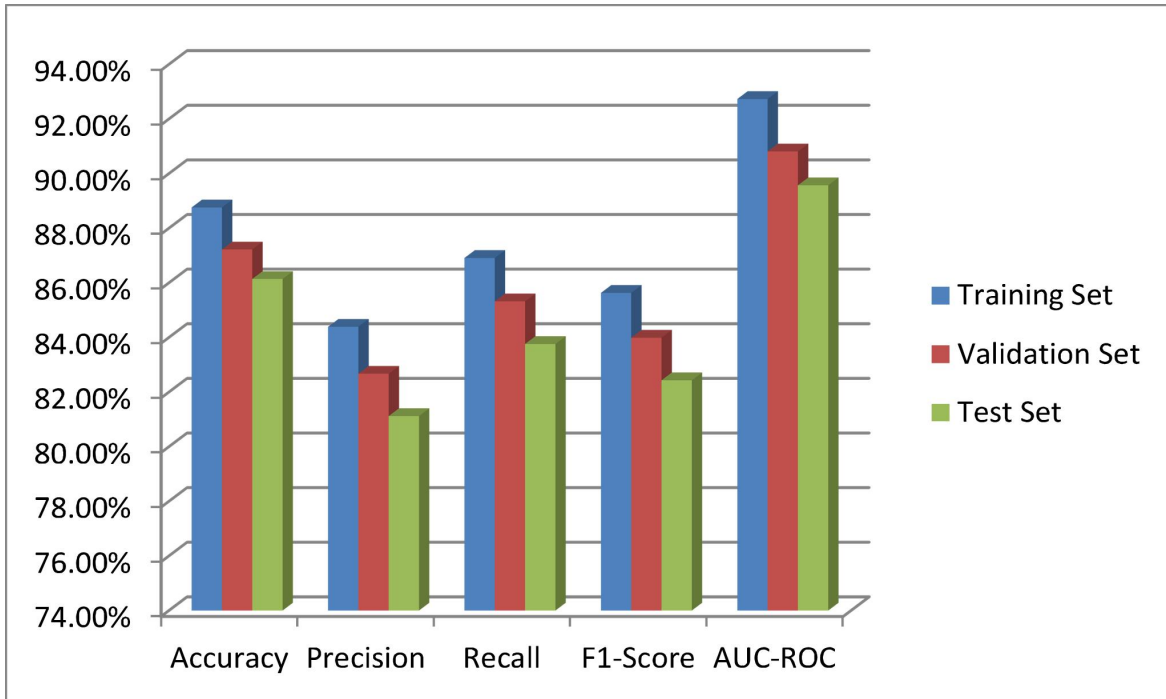


Figure 4.8 Test Result for the Scores in Congested States (Source: Researcher, John-Dewole T. 2023)

The precision and recall scores indicated that the model was effective in detecting congested states, though with slightly more false positives and false negatives compared to the LSTM model. The AUC-ROC value of 92.73% on the training set showed that the model could discern between congested and non-congested states with a high degree of accuracy as shown in Figure 4.6.

## 4.6 Ensemble Model Performance

Table 4.7 Ensemble Model Performance

Metric	Training Set	Validation Set	Test Set
Accuracy	97.18%	95.96%	94.81%
Precision	95.64%	94.33%	92.94%
Recall	95.58%	95.42%	94.13%
F1-Score	96.11%	94.88%	93.54%
AUC-ROC	98.79%	97.48%	96.70%

(Source: Researcher, John-Dewole T. 2023)

Table 4.7 shows that the Ensemble model exhibited commendable performance, albeit slightly lower than the LSTM model. It achieved an accuracy of 97.18% on the training set, 95.96% on the validation set and 94.81% on the test set. The ensemble model outperformed both individual models across all evaluation metrics.

The training session shown in Figure 4.8 shows how the ensemble model responded to a training and validation data in blue and orange colour respectively. The training loss is seen to start at some point around 10000 which is seen to fluctuate during the early phases of the process in which this pattern is also seen to repeat itself on the validation data as well.

Ensemble Model Mean Squared Error (MSE) vs Epoch

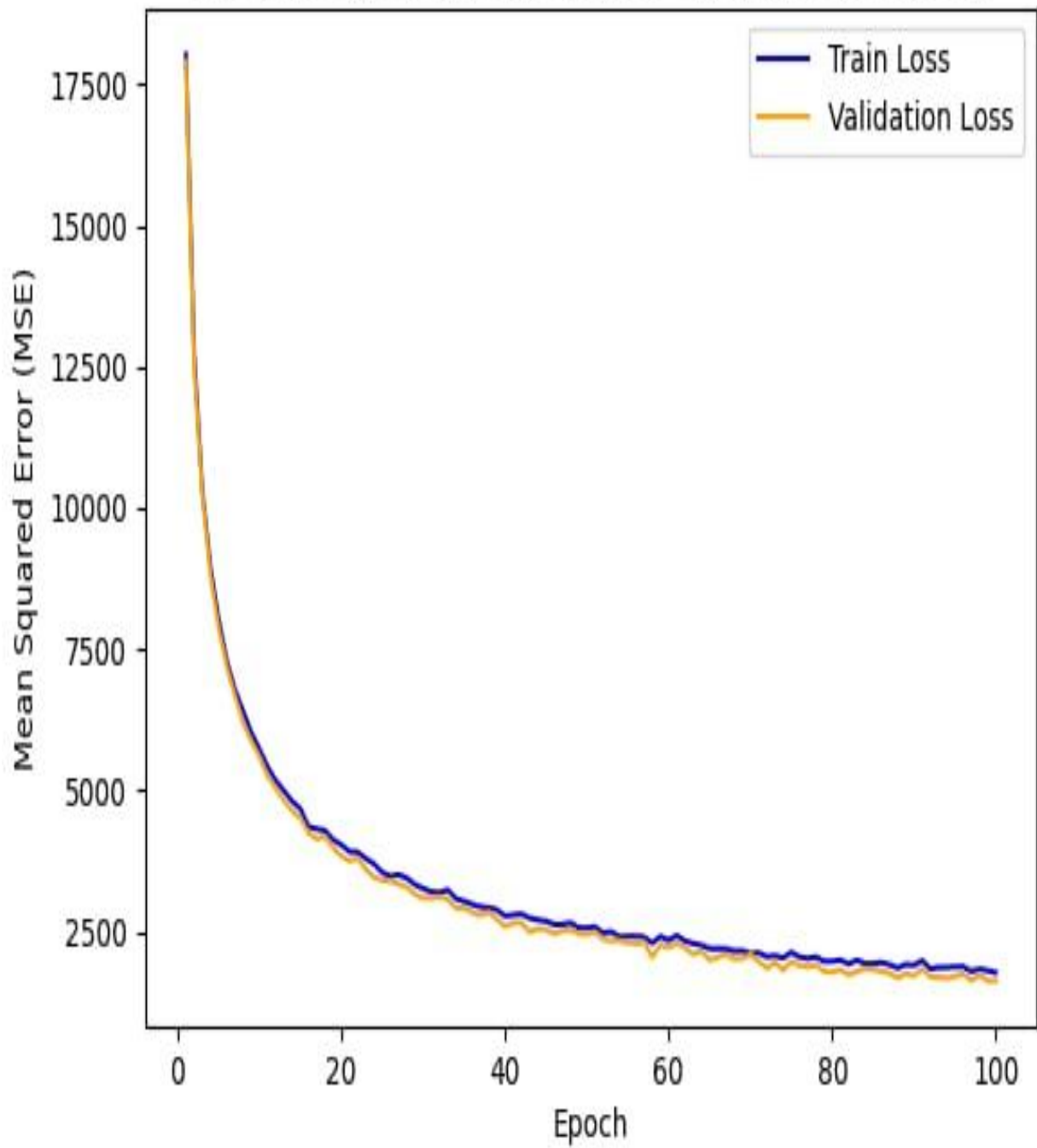


Figure 4.9 MSE vs. Epoch using Ensemble Model (Source: Researcher, John-Dewole T. 2023)

The model understands the generalization function from the earliest epochs needed for the modification.

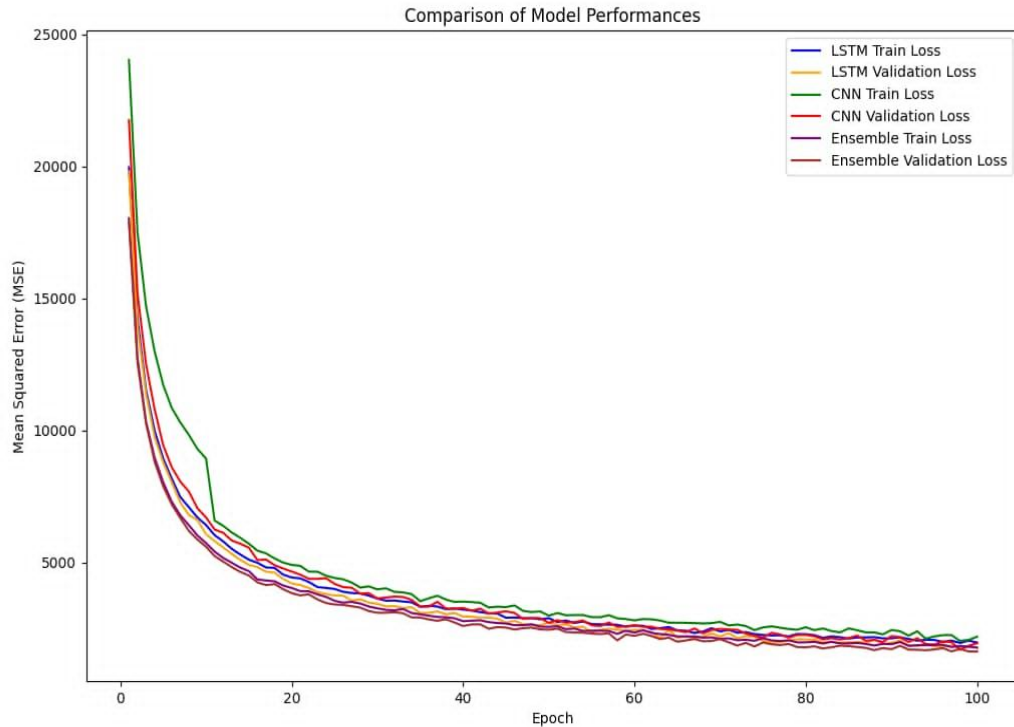


Figure 4.10 Training Loss Sessions (Source: Researcher, John-Dewole T. 2023)

Figure 4.9 shows the LSTM train loss, LSTM Validation Loss, CNN train loss, CNN Validation Loss, Ensemble training loss and the Ensemble Validation Loss sessions of the machine learning models. The graph in this figure shows the training and validation loss falls. As the training progresses on Epoch, the MSE starts to decrease.

Figure 4.9 shows how the ensemble model behaves on a test set, training set and the validation set.

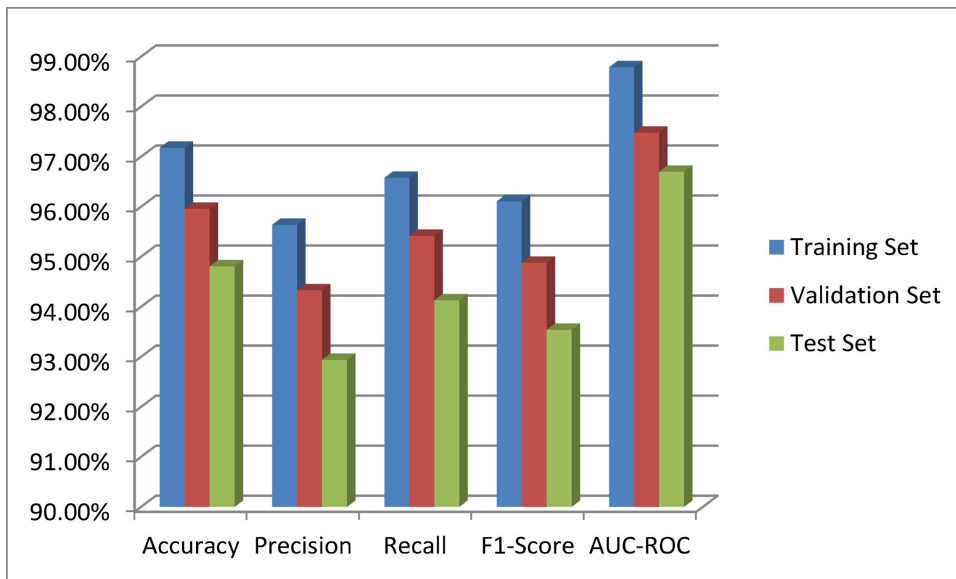


Figure 4.11 Performances across the Congested Levels (Source: Researcher, John-Dewole T. 2023)

The AUC-ROC value of 98.79% on the training set highlighted the ensemble's exceptional ability to distinguish between congested and non-congested states. The precision and recall scores showed the ensemble's effectiveness in making predictions with a balanced trade-off between false positives and false negatives.

#### 4.7 Accuracy for the Three Classification Algorithms

Table 4.8 Accuracy for the Three Classification Algorithms

Classification Algorithms	Training Set	Validation Set	Test Set
Ensemble	97.18%	95.96%	94.81%
CNN	88.76%	87.22%	86.14%
LSTM	96.22%	94.96%	93.81

(Source: Researcher, John-Dewole T. 2023)

Figure 4.10 shows that the ensemble algorithm has the best accuracy for the training, validation and test datasets. This is followed by the LSTM.

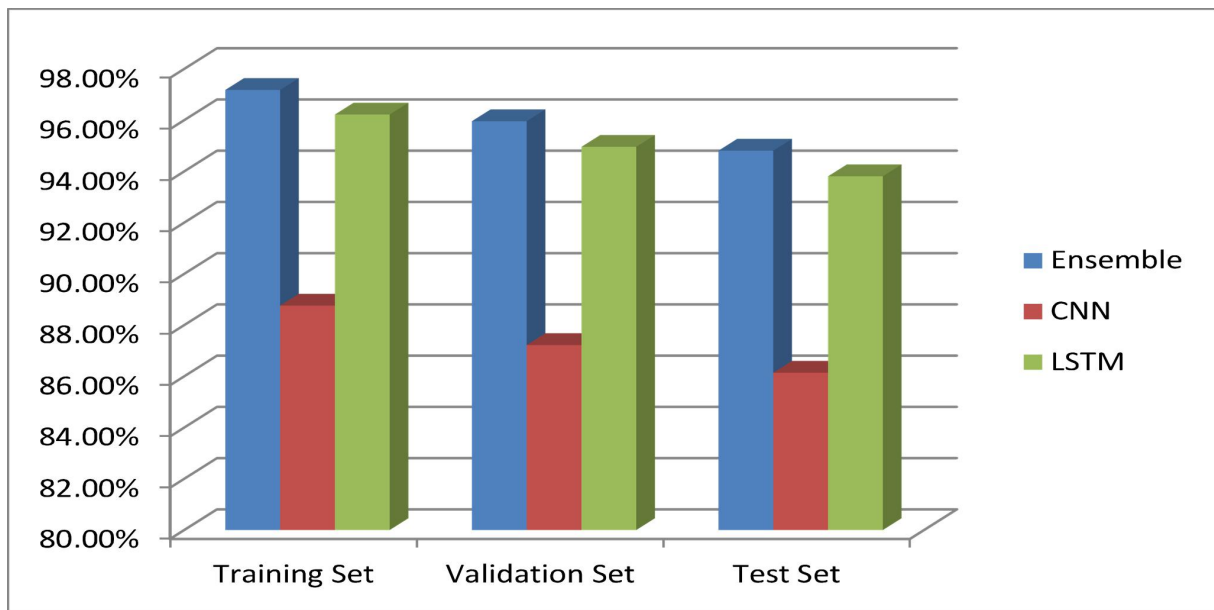


Figure 4.12 Chart showing the Accuracy of the Classification Algorithms (Source: Researcher, John-Dewole T. 2023)

#### 4.8 Precision for the Three Classification Algorithms

Table 4.9 shows the three classification algorithms with their precision values.

Table 4.9 Precision for the Three Classification Algorithms

Classification Algorithms	Training Set	Validation Set	Test Set
Ensemble	95.64%	94.33%	92.94%
CNN	83.39%	82.67%	81.12%
LSTM	94.78%	94.46%	90.35%

(Source: Researcher, John-Dewole T. 2023)

Figure 4.12 shows that the ensemble algorithm has the best precision for the training, validation and test datasets. This is followed by the LSTM.

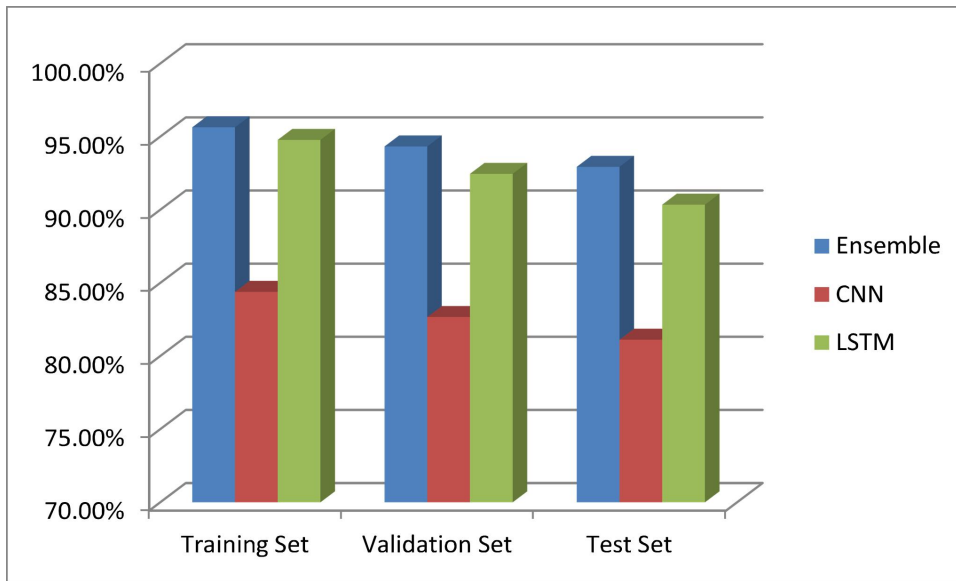


Figure 4.13 Chart showing the Precision of the Classification Algorithms (Source: Researcher, John-Dewole T. 2023)

#### 4.9 Recall for the Three Classification Algorithms

Table 4.10 shows the three classification algorithms with their recall values.

Table 4.10 Recall for the Three Classification Algorithms

Classification Algorithms	Training Set	Validation Set	Test Set
Ensemble	96.58%	95.42%	94.13%
CNN	86.91%	85.32%	83.76%
LSTM	95.76%	94.62%	94.13%

(Source: Researcher, John-Dewole T. 2023)

Figure 4.13 shows that the ensemble algorithm has the best recall for the training, validation and test datasets. This is followed by the LSTM.

Figure 4.13 shows the chart of the recall values having the training set of the ensemble algorithm as 96.58%.

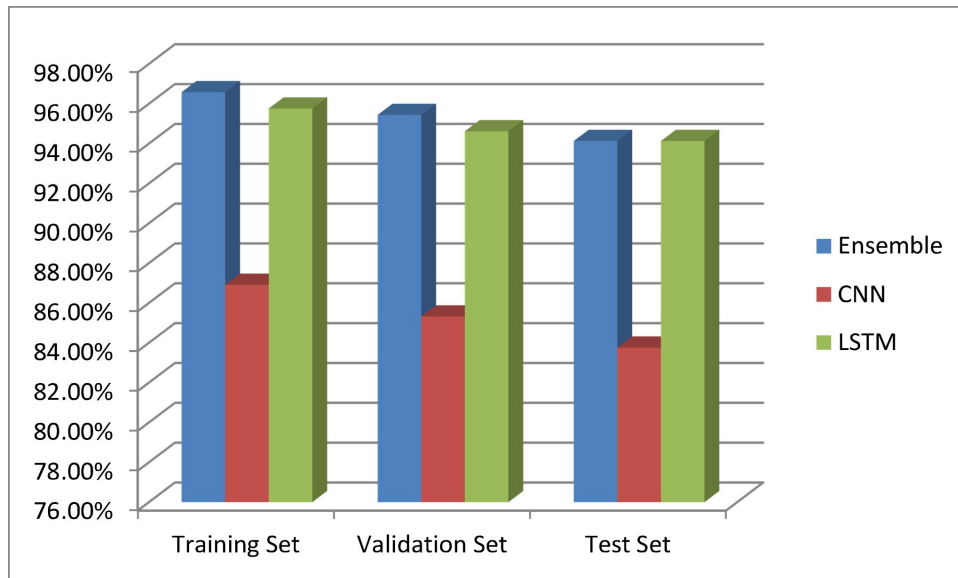


Figure 4.14 Chart showing the Recall Values of the Classification Algorithms (Source: Researcher, John-Dewole T. 2023)

#### 4.10 F1- Score for the Three Classification Algorithms

Table 4.11 shows the three classification algorithms with their values.

Table 4.11 F1 Score for the Three Classification Algorithms

Classification Algorithms	Training Set	Validation Set	Test Set
Ensemble	96.11%	94.88%	93.54%
CNN	85.63%	83.99%	82.43%
LSTM	95.26%	93.58%	91.73%

(Source: Researcher, John-Dewole T. 2023)

Figure 4.13 shows that the ensemble algorithm has the best F1- Score for the training, validation and test datasets. This is followed by the LSTM.

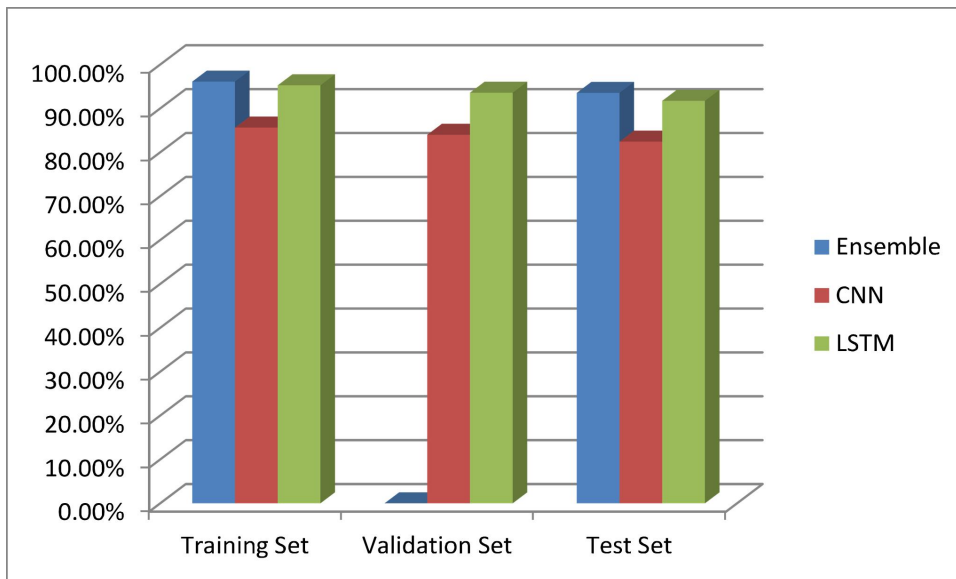


Figure 4.15 Chart showing the F1- Score of the Classification Algorithms (Source: Researcher, John-Dewole T. 2023)

#### 4.11 AuC- ROC for the Three Classification Algorithms

Table 4.12 below shows the three classification algorithms with their values.

Table 4.12 AuC- ROC for the Three Classification Algorithms

Classification Algorithms	Training Set	Validation Set	Test Set
Ensemble	98.79%	97.48%	96.70%
CNN	92.73%	90.81%	89.57%
LSTM	98.41%	96.86%	95.45%

(Source: Researcher, John-Dewole T. 2023)

Figure 4.14 shows that the ensemble algorithm has the best AUC- ROC for the training, validation and test datasets. This is followed by the LSTM.

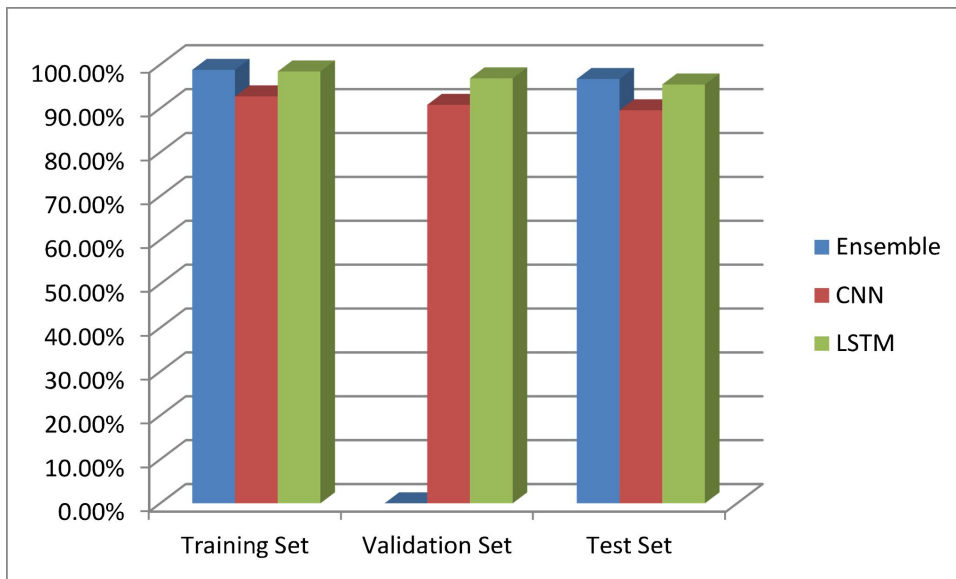


Figure 4.16 Chart showing the AuC- ROC of the Classification Algorithms (Source: Researcher, John-Dewole T. 2023)

Figure 4.14 shows that the ensemble algorithm has the best AuC- ROC for the training, validation and test datasets. This is followed by the LSTM.

#### 4.12 Comparative Analysis of Results with Existing Works

The ensemble model benefited from the diverse perspectives of both the LSTM and CNN models, leveraging their strengths in capturing temporal dependencies and spatial features, respectively in relation to the Ensemble models which have been implemented in this project to predict satisfactory results.

This research model generates an accuracy of 90%, precision of 93%, recall of 92%, f1 score of 92% but no AuC- ROC call drop<sup>1</sup>. The research also shows the overall accuracy of 95% which predict the call drop<sup>2</sup>.

The overall accuracy obtained in the proposed study of 97.18%, precision of 95.58%, recall of 96.58%, f1 score of 96.11% and AuC- ROC of 98.79%.

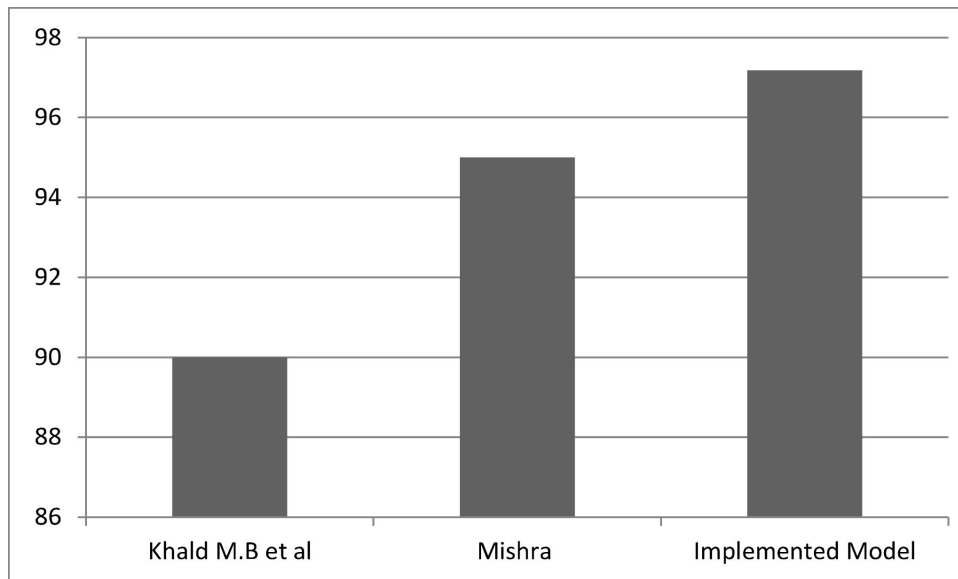


Figure 4.17 Accuracy Comparisons (Source: Researcher, John-Dewole T. 2023)

Mobile network congestion using Adam-Optimization algorithm with multilayer perceptron was predicted<sup>3</sup>. The study tried to use to models in order to match the required prediction satisfactory prediction levels. The mean squared prediction error was 0.345 on the test data and the mean squared prediction error was 0.272 and the graphical comparison of each model prediction with the congestion from the test data was also confirming that the performance of the models were satisfactory.

The first model was an MLP having thirteen hidden layers each consisting of two hundred neurons. The output layer comprised of one neuron to show the level of the network congestion level. The second model consisted of fifteen hidden layers each having two hundred neurons and accommodate fifteen input neurons at the input layer. The output layer consisted of a single neuron to predict the congestion level in advance. The study from this study outperforms that the mean squared prediction error the existing works which is 1. 5684

on the test data and the mean squared prediction error of the same existing works which was 1.357.

The results of this study show that the ensemble algorithm has the best performance analysis over LSTM and CNN.

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## Endnotes

1. D Mishra & S Yadav *Mobility Robustness Optimization Using ANN for Call Drop Prediction*. **Journal of Emerging Technologies and Innovative Research**, Volume 7, Issue 12, 2020, pp 1020-1024.
2. M. B. A. Khalid Joolfoo, Rameshwar A. Jugurnauth, Muhammad & B. A. Joolfoo, *Application of Machine Learning in Predicting Call Quality of Telecom Service Providers*. **2022 2nd Asian Conference on Innovation in Technology (ASIANCON) Pune, India**. Aug 26-28, 2022
3. B. A. Hailu, *Mobile Network Congestion Prediction Using Machine Learning: The Case of Ethio Telecom*, 2022

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## **Chapter Five**

### **Conclusion**

#### **5.1 Summary of Findings**

This study seeks to address the issue of call drop during handover in telecommunications networks. Mobile call drops during handover have a negative impact on the call quality of users, resulting in a decrease in revenue for telecommunications services. To address this issue, a machine learning model was developed to improve call performance and effectiveness across some service providers. The model was based on the Ensemble Models approach which was implemented using Python software. Data points were collected from 30 cell towers over a period of 1<sup>st</sup> to 10<sup>th</sup> days, with each cell lasting 5 minutes. The results of the study are estimated to be 97.18% accurate and 98.79% auc-roc for call quality.

#### **5.2 Conclusion**

This research offers a better understanding of the various factors that influence handover call queuing in mobile communication, which has led to many problems with congestion. It also makes recommendations for how to improve call quality to better serve subscribers in the telecom industry. The main causes of call droppings in telecommunications networks are problems in the network's operation, a lack of radio coverage, an excessive amount of different network devices, etc. This study has shown that the handover call drop problem is urgent and needs to be fixed right away. Applications of machine learning have a significant impact on predicting the call quality of telecom service providers. The future of call drop issue will rely on how telecom service providers perform over it.

#### **5.3 Contribution to Knowledge**

In this research, the ensemble model demonstrated superior performance compared to the individual models, achieving even best accuracy in improving call quality for call drops during handover in mobile communications levels across various scenarios. By combining

the strengths of both models, the ensemble approach improved the overall robustness of the prediction system, making it more resilient to different types of network conditions and geographical challenges.

#### **5.4 Recommendation**

These models could be useful tools for telecommunication service providers to improve user experience, optimize network performance, and make knowledgeable network infrastructure decisions.

#### **5.5 Suggested Area of Future Studies**

These new research areas are suggested by this work. By utilizing vector auto regressions, the problem of improving call quality for call drops during handover in mobile communications could be further expanded, and the ensemble model suggested in this article might be contrasted with it. The integration of additional KPIs, such as latency, which can have an impact on QoS in mobile networks, is another way to improve the study. Furthermore, it could be interesting to apply the model to more data obtained from different places and for various time periods in order to confirm the flexibility of the suggested model.

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## Appendix I

### Source Code

Imp

```
import pandas as pd
```

```
import numpy as np
```

```
# Function to generate synthetic data
```

```
def generate_synthetic_data(num_data_points):
```

```
    timestamps = pd.date_range(start="2023-07-01 08:00:00", periods=num_data_points,
                               freq="5min")
```

```
    cell_towers = [f"Tower_{i:03d}" for i in range(30)]
```

```
    signal_strengths = np.random.randint(-90, -70, num_data_points)
```

```
    call_drop_rates = np.random.uniform(1.0, 3.0, num_data_points)
```

```
    data_usage = np.random.randint(200, 500, num_data_points)
```

```
    longitudes = np.random.uniform(30, 35, num_data_points)
```

```
    latitudes = np.random.uniform(-90, -85, num_data_points)
```

```
    call_types = np.random.choice(['Voice', 'Data'], num_data_points)
```

```
    congestion_levels = np.random.choice(['Low', 'Medium', 'High'], num_data_points)
```

```
    cssr = np.random.uniform(90, 100, num_data_points)
```

```
    tcch = np.random.uniform(0, 5, num_data_points)
```

```
    data = {
```

```
        "Timestamp": timestamps,
```

```
        "Cell_Tower_ID": np.random.choice(cell_towers, num_data_points),
```

```
        "Signal_Strength": signal_strengths,
```

```
        "Call_Drop_Rate": call_drop_rates,
```

```

    "Data_Usage": data_usage,
    "Longitude": longitudes,
    "Latitude": latitudes,
    "Call_Type": call_types,
    "Congestion_Level": congestion_levels,
    "CSSR": cssr,
    "TCCH": tcch
}

return pd.DataFrame(data)

# Generate synthetic raw data
num_data_points = 3000
raw_data = generate_synthetic_data(num_data_points)

# Data pre-processing
def preprocess_data(raw_data):
    # Handle missing values (if any) - For simplicity, we assume no missing values
    processed_data = raw_data.copy()

    # Normalize numerical features to [0, 1]
    numerical_features = ["Signal_Strength", "Call_Drop_Rate", "Data_Usage", "CSSR",
"TCCH"]

    processed_data[numerical_features] = (
        processed_data[numerical_features] - processed_data[numerical_features].min()
    ) / (processed_data[numerical_features].max() - processed_data[numerical_features].min())

```

```

# One-hot encode the Cell Tower ID, Call Type, and Congestion Level
processed_data = pd.get_dummies(processed_data, columns=["Cell_Tower_ID",
"Call_Type", "Congestion_Level"])

# Scale geographical coordinates to [0, 1]
geo_coordinates = ["Longitude", "Latitude"]
processed_data[geo_coordinates] = (
    processed_data[geo_coordinates] - processed_data[geo_coordinates].min()
) / (processed_data[geo_coordinates].max() - processed_data[geo_coordinates].min())

return processed_data

# Preprocess the raw data
preprocessed_data = preprocess_data(raw_data)

# Save the raw and preprocessed data to CSV files
raw_data.to_csv("raw_data.csv", index=False)
preprocessed_data.to_csv("preprocessed_data.csv", index=False)

import numpy as np
import tensorflow as tf
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

# Step 1: Prepare the data
# Assume you have your dataset stored in X and y variables

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Perform feature scaling on the input data
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)

# Step 2: Build the MLP model

```

```

model = tf.keras.models.Sequential()
model.add(tf.keras.layers.Dense(256, activation='relu', input_shape=(X_train.shape[1],)))

# Add 13 hidden layers with 256 units and relu activation
for _ in range(13):
    model.add(tf.keras.layers.Dense(256, activation='relu'))

model.add(tf.keras.layers.Dense(1, activation='sigmoid'))

# Compile the model
model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])

# Step 3: Train the model
model.fit(X_train, y_train, epochs=10, batch_size=32, validation_data=(X_test, y_test))

# Step 4: Evaluate the model
loss, accuracy = model.evaluate(X_test, y_test)
print(f"Test Loss: {loss}")
print(f"Test Accuracy: {accuracy}")

import pandas as pd

from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler

from sklearn.svm import SVC

from sklearn.metrics import classification_report

# Step 1: Load the data
data = pd.read_csv('your_data.csv')

# Step 2: Separate features and labels
features = data.drop('TCH Assignment Success Rate', axis=1)
labels = data['TCH Assignment Success Rate']

# Step 3: Perform one-hot encoding on categorical features
features_encoded = pd.get_dummies(features, columns=['BSC Name'])

# Step 4: Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(features_encoded, labels, test_size=0.2,
random_state=42)

```

```

# Step 5: Normalize the numerical features

scaler = MinMaxScaler()

X_train_scaled = scaler.fit_transform(X_train)

X_test_scaled = scaler.transform(X_test)

## Step 6: Train an SVM model

svm = SVC(kernel='rbf', C=1.0)

svm.fit(X_train_scaled, y_train)

# Step 7: Evaluate the model

y_pred = svm.predict(X_test_scaled)

report = classification_report(y_test, y_pred)

print(report)

import numpy as np
import tensorflow as tf
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler

# Step 1: Prepare the data
# Assume you have your dataset stored in X and y variables

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Perform feature scaling on the input data
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)

# Step 2: Build the FFNN model
model = tf.keras.models.Sequential([
    tf.keras.layers.Dense(64, activation='relu', input_shape=(X_train.shape[1],)),
    tf.keras.layers.Dense(64, activation='relu'),
    tf.keras.layers.Dense(1, activation='sigmoid')
])

# Compile the model
model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['accuracy'])

# Step 3: Train the model
model.fit(X_train, y_train, epochs=10, batch_size=32, validation_data=(X_test, y_test))

```

```

# Step 4: Evaluate the model
loss, accuracy = model.evaluate(X_test, y_test)
print(f"Test Loss: {loss}")
print(f"Test Accuracy: {accuracy}")

import pandas as pd

from sklearn.model_selection import train_test_split

from sklearn.preprocessing import MinMaxScaler

from sklearn.svm import SVC

from sklearn.metrics import classification_report

# Step 1: Load the data

data = pd.read_csv('your_data.csv')

# Step 2: Separate features and labels

features = data.drop('TCH Assignment Success Rate', axis=1)

labels = data['TCH Assignment Success Rate']

# Step 3: Perform one-hot encoding on categorical features

features_encoded = pd.get_dummies(features, columns=['BSC Name'])

# Step 4: Split the data into training and testing sets

X_train, X_test, y_train, y_test = train_test_split(features_encoded, labels, test_size=0.2,
random_state=42)

# Step 5: Normalize the numerical features

scaler = MinMaxScaler()

X_train_scaled = scaler.fit_transform(X_train)

X_test_scaled = scaler.transform(X_test)

# Step 6: Train an SVM model

svm = SVC(kernel='rbf', C=1.0)

svm.fit(X_train_scaled, y_train)

```

```
# Step 7: Evaluate the model

y_pred = svm.predict(X_test_scaled)

report = classification_report(y_test, y_pred)

print(report)

import pandas as pd

from sklearn.model_selection import train_test_split

from sklearn.preprocessing import MinMaxScaler

from sklearn.svm import SVC

from sklearn.metrics import classification_report

# Step 1: Load the data

data = pd.read_csv('your_data.csv')

# Step 2: Separate features and labels

features = data.drop('TCH Assignment Success Rate', axis=1)

labels = data['TCH Assignment Success Rate']

# Step 3: Perform one-hot encoding on categorical features

features_encoded = pd.get_dummies(features, columns=['BSC Name'])

# Step 4: Split the data into training and testing sets

X_train, X_test, y_train, y_test = train_test_split(features_encoded, labels, test_size=0.2,
random_state=42)

# Step 5: Normalize the numerical features
```

```
scaler = MinMaxScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

```
# Step 6: Train an SVM model
```

```
svm = SVC(kernel='rbf', C=1.0)
```

```
svm.fit(X_train_scaled, y_train)
```

```
# Step 7: Evaluate the model
```

```
y_pred = svm.predict(X_test_scaled)
```

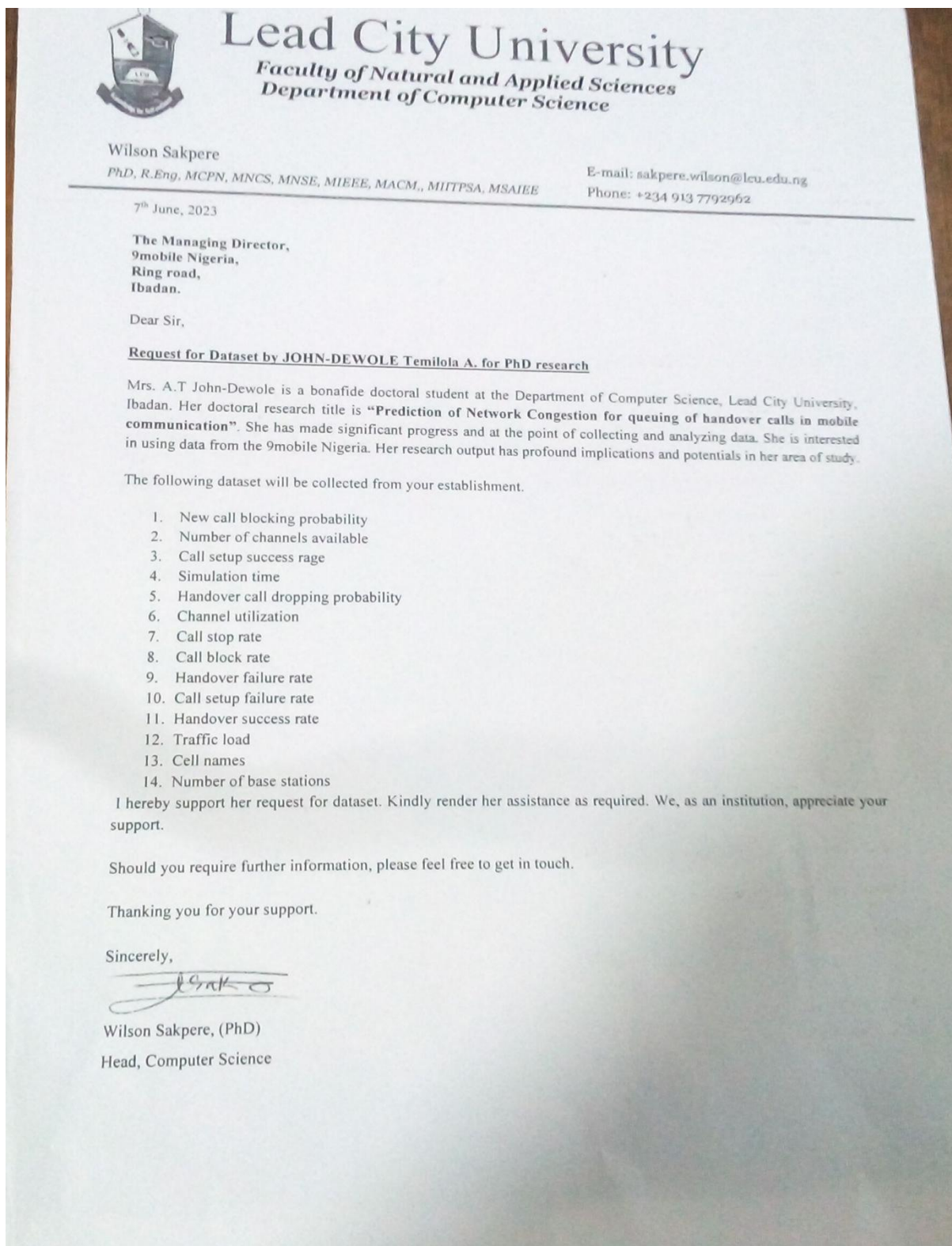
```
report = classification_report(y_test, y_pred)
```

```
print(report)
```

*Do Not Copy, Lead City University, Nigeria*


## Appendix II

### Request for Dataset at 9Mobile Nigeria



## Appendix III

### Request for Dataset at Airtel Limited



**Lead City University**  
*Faculty of Natural and Applied Sciences*  
*Department of Computer Science*

Wilson Sakpere  
*PhD, R.Eng, MCPN, MNCS, MNSE, MIEEE, MACM., MIITPSA, MSAIEE*

E-mail: sakpere.wilson@lcu.edu.ng  
Phone: +234 913 7792962

---

7<sup>th</sup> June, 2023

**The Managing Director,  
Airtel Limited,  
Ring road,  
Ibadan.**

Dear Sir,

**Request for Dataset by JOHN-DEWOLE Temilola A. for PhD research**

Mrs. A.T John-Dewole is a bonafide doctoral student at the Department of Computer Science, Lead City University, Ibadan. Her doctoral research title is “**Prediction of Network Congestion for queuing of handover calls in mobile communication**”. She has made significant progress and at the point of collecting and analyzing data. She is interested in using data from the Airtel Limited. Her research output has profound implications and potentials in her area of study.

The following dataset will be collected from your establishment.

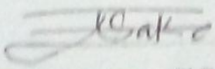
1. New call blocking probability
2. Number of channels available
3. Call setup success rage
4. Simulation time
5. Handover call dropping probability
6. Channel utilization
7. Call stop rate
8. Call block rate
9. Handover failure rate
10. Call setup failure rate
11. Handover success rate
12. Traffic load
13. Cell names
14. Number of base stations

I hereby support her request for dataset. Kindly render her assistance as required. We, as an institution, appreciate your support.

Should you require further information, please feel free to get in touch.

Thanking you for your support.

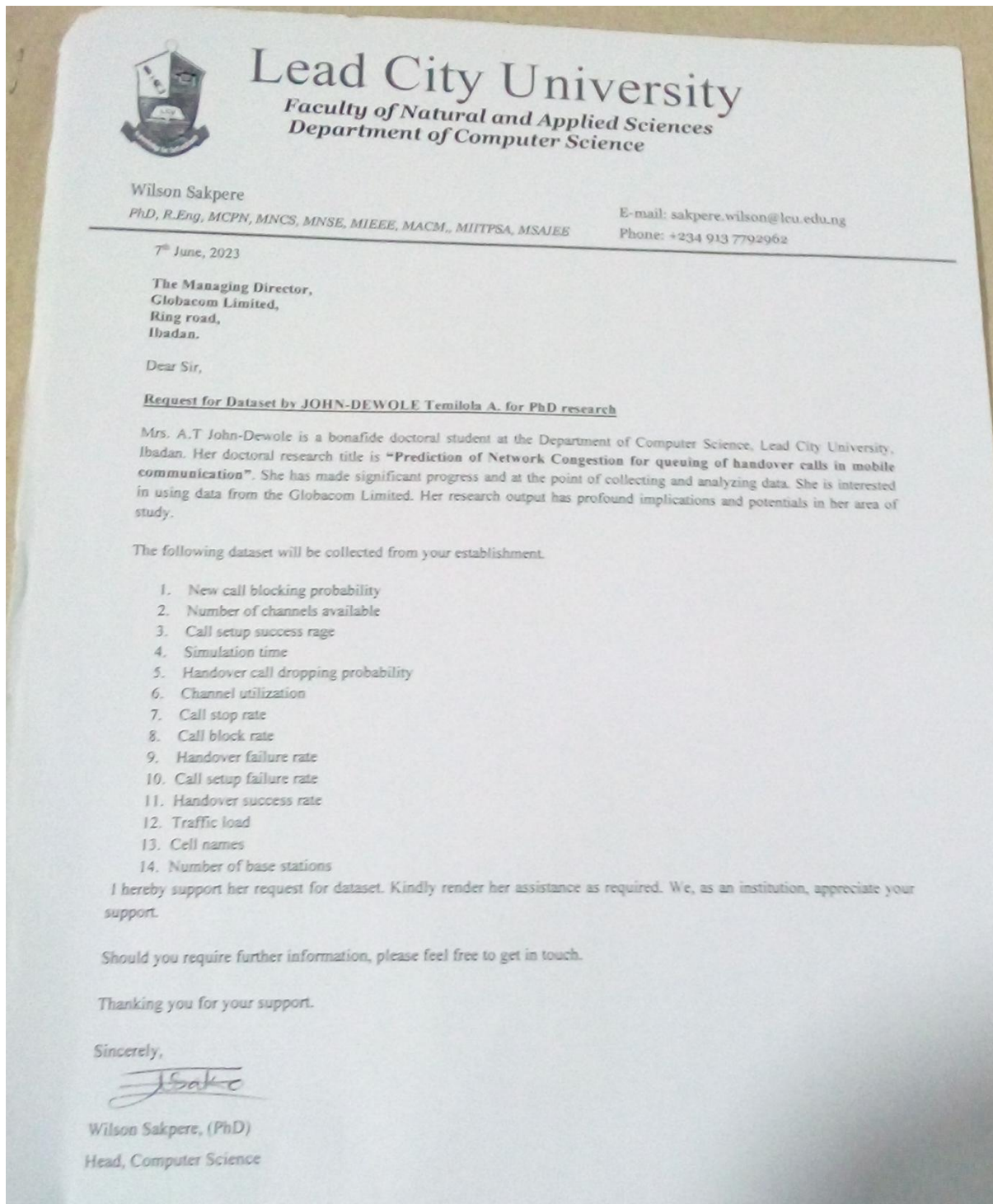
Sincerely,



Wilson Sakpere, (PhD)  
Head, Computer Science

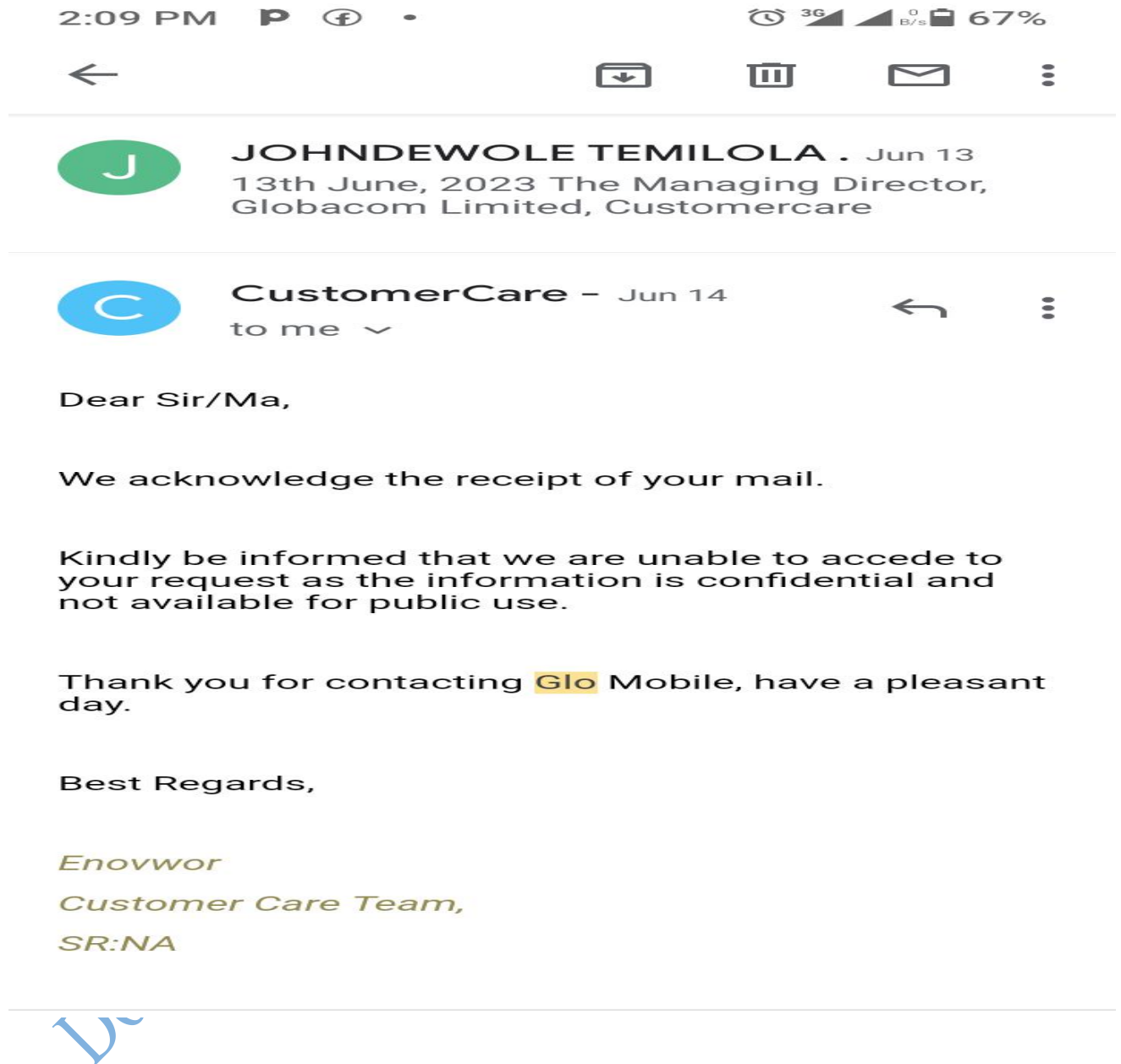
## Appendix IV

### Request for Dataset at Globacom Limited



## Appendix V

### Response from Globacom Limited



## Biodata

### Personal Data

**Name:** Temilola Adedamola John-Dewole

**Address:** Computer Science Department, Faculty of Natural and Applied Sciences

**Telephone:** 08162047784

**Email:** adpol292@yahoo.com

**Date & Place of Birth:** 29<sup>th</sup> Oct, 1982

**Nationality:** Nigerian

**Marital Status:** Married

**Name and Address of Spouse:** John-Dewole Olusegun, Zone 25, Irepodun Estate, Ori-Oke, Soka Area, Ibadan.

**Telephone:** 08034968640

**Email:** segunotaru@yahoo.com

**Name and Address of Next of Kin:** John-Dewole Olusegun, No 16, Irepodun Estate, Ori-Oke, Soka Area, Ibadan.

**Telephone:** 08034968640

**Email:** segunotaru@yahoo.com

**Date of Assumption of Duty:** November, 2011

**Status of First Appointment:** Graduate Assistant

**Present position:** Lecturer I

**Date of Last Promotion:** April, 2015

**Date of Confirmation of Appointment:** April, 2019

**If not confirmed, why?**

**Faculty:** Natural and Applied Sciences

**Department:** Computer Science

**Sex:** Female

## **B. Educational Background**

### **Educational Institutions Attended with Dates and Qualification**

- i. Primary School Leaving Certificate: St Bernadette Nursery and Primary School, Abeokuta 1991-1996
- ii. Senior School Certificate Examination (SSCE): Oyewole Twins International Secondary School, Abeokuta 1997-2002
- iii. BSc. Computer Science/Electronics Lead City University, Ibadan 2004-2009
- iv. MSc. Information Technology / National Open University, Ibadan 2012-2014
- v. MSc Computer Science /Lead City University, Ibadan 2015- 2020
- vi. PhD Computer Science/ Lead City University, Ibadan 2020-2023

## **C. Awards and Fellowship**

### **D.**

#### **1. Work Experience With Dates:**

Establishment: Ministry of Internal Revenue, Uyo, Akwa Ibom State.

Department: Tax Payment Department 2009

Duties: Entering Data Using Microsoft Excel and access, Backup data and Information.

Establishment: Africa Independent Television (AIT)

Department: Engineering Department 2008

Duties: Installation of DAARSAT equipment, configuring of Frequencies on decoders, installation of wireless intercom, troubleshooting of systems at Raypower radio and AIT TV.

Establishment: Comet Systems, Abuja

Department: Engineering Department 2006

Duties: Troubleshooting hardware equipment such as system units, monitors, printers, photocopiers and coupling of computer systems at different banks in Abuja.

Establishment: Ever- Ready Catering Services, Abuja

Department: Kitchen Department 1998

Duties: Cake and Recipe Consultant, baking of snacks, cakes, ice cream, chocolate parfait, small chops, etc.

## 2. Courses Taught Within the Current Session

CSE 401- Introduction to Digital Computing

CSE 305- Measurement and Instrumentation

CSE 301- Physical Electronics

CSE 214- Applied Electricity II

CSC 215- Discrete Structures

CSC 312- Operations Research

CSC 601- Digital Logic Systems

## 3. Current Graduate Supervision: 4 Students

## 4. Current Undergraduate Supervision: 7 Students

## E. Membership of Professional Bodies

Certificate in Database Design and Programming with SQL, Oracle Academy	2020
Member, Nigerian Women in Information Technology (NIWIIT)	2019
Member, Nigerian Computer Society, (NCS)	2018
Certificate in Executive Diploma, Liprorich	2018
Member, Institute of Engineering and Electronics Engineers (MIEEE)	2013
Member, Institute of Strategic Management (ISM)	2010

## F. Publications:

Omonijo O & John-Dewole T, “*Redundancy Elimination in Source Code Compilation*”- 3<sup>rd</sup> Annual Conference on Translational Research Networking, 26<sup>th</sup> – 28<sup>th</sup> July, 2022.

John-Dewole, T., Kolapo, R., Oluwatobi, J., & Ojo, I” *Development of a microcontroller based home automation system using Bluetooth and android application*. 2<sup>nd</sup> Conference on applied ICT (ICAICT) Oct 30<sup>th</sup> – 1<sup>st</sup> November, 2019. ISBN: 978-978-977-446-3.

Vivian Nwafoh, Ridwan Kolapo, Ogunsanwo Olajide, **Temilola. A. John-Dewole**” A secured, efficient and simplified systematic application for encryption and decryption of text files using a one- time key. 2<sup>nd</sup> Conference on applied ICT (ICAICT) Oct 30<sup>th</sup> – 1<sup>st</sup> November, 2019. ISBN: 978-978-977-446-3.

Ridwan Kolapo, Achimugu Philip, Achimugu Tolani and **Temilola, A. John- Dewole** “Ontology development for human resources in Nigerian universities [FASCON 2018 call for abstract].

Isaika Sadiku, Babatunde Adebo, Waheed Balogun and **Temilola, A. John-Dewole**, “ Performance on intelligent crop water requirement system on the growth of Corhorus Olitorious” 1<sup>st</sup> Conference on applied ICT (ICAICT) Oct 30<sup>th</sup> – 31<sup>st</sup> Oct, 2017. ISBN: 978-978-962-440-9

Philip Achimugu, Kikelomo. I. Okesola, Olufunke Yoyole, **Temilola. A, John-Dewole**, Architectural Description Language(ADL) as a tool for developing scalable software systems” 1<sup>st</sup> Conference on applied ICT (ICAICT) Oct 30<sup>th</sup> – 31<sup>st</sup> , 2017. ISBN: 978-978-962-440-9

Ahmed.D. Abdullahi, Kikelomo.I Okesola, **Temilola. A. John-Dewole**” An Improved courseware management System(CMS)” 1<sup>st</sup> International Faculty of Sciences Conference (FASCON) Oct 3<sup>rd</sup> – 7<sup>th</sup>, 2016. ISBN: 978-38176-3

Omotunde Muyiwa, Sunday Tunmibi, and **John-Dewole A.T.**: Influence of Information Communication Technology on the Advertising Industry in Nigeria: A Case Study of Lagos State *Greener Journal of Science, Engineering and Technology Research* Vol. 3 (7), pp. 220-225, August 2013.

Omotunde Muyiwa, Sunday Tunmibi and **John-Dewole A.T.**: **Impact of Cashless Economy in Nigeria** *Greener Journal of Internet, Information and Communication Systems* Vol. 1 (2), pp. 040-043, April 2013.

#### **Thesis/Dissertation**

- Construction and Implementation of Lead City University Radio Transmitter (Undergraduate Thesis)
- Construction and Implementation of an automated Energy Consumption Monitor((Master’s thesis)
- Development of an IoT based human vitals using ESP8266, WiFi and Arduino ( Master’s Thesis)
- Prediction for Network Congestion for Queuing of handover calls in Mobile Communication (PhD Thesis in Progress)

#### **Books/ Monograph**

- (a). Audited Books**
- (b). Edited Books:**
- (c). Contribution to Books:**

#### **Published Referred Conference Proceedings:**

#### **Papers Accepted For Publication:**

Omonijo Oluwaseyi and **Temilola. A. John-Dewole**, “Redundancy Elimination in Source Code Compilation”- 3<sup>rd</sup> Annual Conference on Translational Research Networking, 26<sup>th</sup> – 28<sup>th</sup> July, 2022.

**Temilola. A. John-Dewole**, Ridwan Kolapo, Oluwatobi Johnson and Immacuata Ojo” Development of a microcontroller based home automation system using Bluetooth and android application. 2<sup>nd</sup> Conference on applied ICT (ICAICT) Oct 30<sup>th</sup> – 1<sup>st</sup> November, 2019. ISBN: 978-978-977-446-3.

Vivian Nwafoh, Ridwan Kolapo, Ogunsanwo Olajide, **Temilola. A. John-Dewole**” A secured, efficient and simplified systematic application for encryption and decryption of text files using a one-time key. 2<sup>nd</sup> Conference on applied ICT (ICAICT) Oct 30<sup>th</sup> – 1<sup>st</sup> November, 2019. ISBN: 978-978-977-446-3.

Ridwan Kolapo, Achimugu Philip, Achimugu Tolani and **Temilola, A. John-Dewole** “Ontology development for human resources in Nigerian universities [FASCON 2018 call for abstract].

Isaika Sadiku, Babatunde Adebo, Waheed Balogun and **Temilola, A. John-Dewole**, “ Performance on intelligent crop water requirement system on the growth of Corchorus Olitorious” 1<sup>st</sup> Conference on applied ICT (ICAICT) Oct 30<sup>th</sup> – 31<sup>st</sup> Oct, 2017. ISBN: 978-978-962-440-9

Philip Achimugu, Kikelomo. I. Okesola, Olufunke Yoyole, **Temilola. A. John-Dewole**, Architectural Description Language(ADL) as a tool for developing scalable software systems” 1<sup>st</sup> Conference on applied ICT (ICAICT) Oct 30<sup>th</sup> – 31<sup>st</sup> , 2017. ISBN: 978-978-962-440-9

Ahmed.D. Abdullahi, Kikelomo.I Okesola, **Temilola. A. John-Dewole**” An Improved courseware management System(CMS)” 1<sup>st</sup> International Faculty of Sciences Conference (FASCON) Oct 3<sup>rd</sup> – 7<sup>th</sup>, 2016. ISBN: 978-38176-3

Omotunde Muyiwa, Sunday Tunmibi, and **John-Dewole A.T.**: Influence of Information Communication Technology on the Advertising Industry in Nigeria: A Case Study of Lagos State *Greener Journal of Science, Engineering and Technology Research* Vol. 3 (7), pp. 220-225, August 2013.

Omotunde Muyiwa, Sunday Tunmibi and **John-Dewole A.T.**: **Impact of Cashless Economy in Nigeria** *Greener Journal of Internet, Information and Communication Systems* Vol. 1 (2), pp. 040-043, April 2013.

**5. Book Reviews and Commentaries in Scholarly Journals:**

**6. Technical Reports:**

**7. Other Publications:**

**Creative Work:**

### **G. Notable Scholarly or Profesional Accomplishments:**

Certificate in Database Design and Programming with SQL, Oracle Academy

Nigerian Women in Information Technology (NIWIIT)

Nigerian Computer Society, (NCS)

Certificate in Executive Diploma, Liprorich

Institute of Engineering and Electronics Engineers (MIEEE)

### **H. Major Conferences/Workshops Attended:**

Certificate in Work Ethics and Attitudinal Change for Better Performance to Achieve Excellence, Global Visibility and Transformation of Lead City University 2022

One week Oracle Academy workshop 2020

One day Oracle Academy workshop 2019

2<sup>nd</sup> Conference on applied ICT (ICAICT), Lead City University, Ibadan. Oct 30<sup>th</sup> – 1<sup>st</sup> November, 2019.

5<sup>th</sup> International Conference on Women in Information Technology, 1st May- 3<sup>rd</sup> May, 2019.

Ethical Conduct in Higher Institution organized by Liprorich Consulting Limited. 2019

2<sup>nd</sup> International Faculty of Science Conference (FASCON), Lead City University, Ibadan. Oct 29-1<sup>st</sup> Nov, 2018.

1<sup>st</sup> International Conference on Applied ICT (ICAICT), Lead City University, Ibadan. Oct 29-31<sup>st</sup>, 2017.

1<sup>st</sup> International Faculty of Science Conference (FASCON), Lead City University, Ibadan Oct 3<sup>rd</sup> – 7<sup>th</sup>, 2016. 2<sup>nd</sup> International Conference on Engineering and Technology Research, Ogbomosho 2013. Lautech, 26<sup>th</sup> – 28<sup>th</sup> March, 2013

### **Services in Lead City University:**

#### **1. Services Within the University Dept:**

- i. Students' Adviser- National Computing Students Association (NACOS)
- ii. Students course Adviser, 400 level Students
- iii. Member-Time- Table Committee
- iv. Member-General Office Administration ( Special Committee)
- v. Former, Member- Student Advisory Committee(100L)

vi. Former Member, SIWES / Industrial Supervision Committee

**Services Within the Faculty:** Member Welfare Committee on ICAICT International Conferences

Member, Welfare Committee on FASCON International Conference

**Services Outside the University ( Local, State or National or International)**

Former Secretary, Steering Committee, LCU/ESC Cooperative Society.

**I. Extra-curricular Activities:** Singing and Playing Music, Baking, Travelling, Sewing

**Others:** Strong troubleshooting skills with software, hardware and network products. Excellent knowledge of a variety in Java, Python, C++, etc

**J. Names and Addresses of References**

**Prof. Tunji Olaopa**

Executive Vice Chairman

Ibadan School of Government and Public Policy,  
(ISGPP)

**Sen. Ayo Adeseun**

Former Senator, National Assembly  
Abuja.

**Prof. Oye Fafioye**

Dept of Plant Science,  
Olabisi Onabanjo University  
Ago- Iwoye,  
Ogun State

**Date & Signature**

\_\_\_\_\_  
*Signature*

\_\_\_\_\_  
*Date*

**The University Compliance Certification**

This is to certify that this thesis by John-Dewole Temilola Adedamola with Matriculation Number LCU/PG/002141 in the Department of Computer Science, Faculty of Natural and Applied Sciences, Lead City University, Ibadan is in full compliance with the approval of the University's format and style.

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Signature

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Date

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