Addis Ababa Institute of Technology
School of Electrical and Computer Engineering
Telecommunication Engineering Graduate Program

Machine Learning-Based Spectrum Utilization Prediction for Dynamic Spectrum Sharing

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A Thesis Submitted to the School of Electrical and Computer Engineering in Partial Fulfillment of the Requirements for the Degree of Master of Science in Telecom Network Engineering

September 29, 2023
Addis Ababa, Ethiopia

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Declaration

I, the undersigned, declare that this thesis is my original work, has not been presented for a degree in this or any other university, and all sources of materials used for the thesis have been fully acknowledged.

Tewodros Abebe ______________________
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Place: Addis Ababa, Ethiopia
Date of Submission: ________________

As a university advisor, I approved the submission of this thesis for examination.

Dr. -Ing. Dereje Hailemariam ______________________
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Abstract

Dynamic Spectrum Sharing (DSS) is a promising technology for improving the performance of heterogeneous wireless networks. DSS allows Fifth Generation New Radio (5G NR) to be deployed in the same frequency bands as Fourth Generation (4G) Long Term Evolution (LTE), which can help to increase cell capacity and improve the overall network performance. Machine Learning (ML) can be used to improve the efficiency of DSS by helping to predict future spectrum utilization and allocate resources accordingly. ML algorithms can be trained on historical data to identify patterns in spectrum usage and learn the behavior of different users. This information can then be used to make predictions about future spectrum utilization and allocate resources accordingly, in a way that minimizes interference and maximizes throughput.

This work proposes an ML-based approach to dynamically distribute spectrum resources between 4G LTE and 5G NR users in a way that meets the traffic requirements of each user and optimizes link-level performance at varying Signal-to-Noise Ratio (SNR) points. Two ML models, namely, Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNN) models are developed for the spectrum utilization prediction.

The Resource Element (RE)-level rate-matching DSS technique is evaluated by using 24-hour sample data from ML prediction results. This thorough assessment encompasses measuring throughput, and spectral efficiency at various SNR points. The proposed model's performance is compared with that of the static spectrum-sharing technique.

The results show that the CNN algorithm-based model can be the best input for the DSS controller to distribute spectrum resources for both technologies optimally. The model can predict the next 6 hours eNodeB (eNB) spectrum utilization with an Root Mean Square Error (RMSE) value of 1.3. Based on the prediction results, the average 4G LTE and 5G NR throughput per day is 8.7 and 107.7216 Mbps, respectively. Furthermore, the overall cell spectral efficiency is increased to 5.82 bits/sec/Hz. LTE performance is not affected by DSS when compared to an existing non-sharing network and Static Spectrum Sharing (SSS). However, NR experiences 32.54% of performance degradation.

The proposed ML-based DSS technique can significantly improve the performance of DSS by dynamically allocating spectrum resources to LTE and 5G NR users. The CNN algorithm-based model is shown to be the best model for spectrum utilization prediction.

Keywords – Dynamic Spectrum Sharing (DSS), Machine Learning (ML), Spectrum Utilization, Long Term Evolution (LTE), and Fifth Generation (5G)

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Dedication

In honor of my family and many friends, I dedicate my thesis work.

Acknowledgment

First and foremost, I would like to express my sincere gratitude to Almighty God for his guidance and strength throughout this journey. I would not have been able to complete this thesis without His help.

I would also like to express my sincere gratitude to my advisor, Dr. –Ing. Dereje Hailemariam, for his invaluable guidance and support. Dr. –Ing. Dereje Hailemariam has been a constant source of inspiration and encouragement, and I am truly grateful for his mentorship.

I am also grateful to Mr. Yibeltal Addis and Mr. Gizachew Hailegebriel for their support in providing data for this study. Their contributions were essential to the success of this research.

I would like to thank Mr. Tibebu Terefe and Mr. Abel Mifta for creating a conducive working environment during thesis time. Their understanding and flexibility allowed me to focus on my research and complete this thesis.

Finally, I would like to express my appreciation to everyone who supported me during the work.

I am genuinely grateful for the support of all of these individuals. Without them, this thesis would not have been possible.

Abbreviation

2G	Second Generation
3GPP	Third Generation Partnership Project
4G	Fourth Generation
5G	Fifth Generation
5G NR	Fifth Generation New Radio
ACM	Adaptive Coding and Modulation
AMF	Access and Mobility management Function
BPSK	Binary Phase-shift keying
BS	Base Station
CDL	Clustered Delay Line
CDL	Clustered Delayed Line
CNN	Convolutional Neural Networks
CP	Cyclic Prefix
CRS	Cell-specific Reference Signals
CSI	Channel State Information
CTCH	Common Transport Channels
DSR	Dynamic Spectrum Refarming
DSS	Dynamic Spectrum Sharing
DTCH	Dedicated Transport Channels
eMBB	enhanced Mobile BroadBand
EMS	Element Management System
eNB	eNodeB
EPC	Evolved Packet Core
EPS	Evolved Packet System
E-UTRAN	Evolved UMTS Terrestrial Radio Access Network
FDD	Frequency Division Duplex

FR	Frequency Ranges
gNB	Next Generation Node B
GSM	Global System for Mobile communication
GSM	Global System for Mobile Communications
HARQ	Hybrid Automatic Repeat Request
IP	Internet Protocol
ITU	International Telecommunications Union
LoS	Line of Sight
LSTM	Long Short Time Memory
LSTM	Long Short-Term Memory
LTE	Long Term Evolution
MAE	Mean Absolute Error
MBSFN	Multimedia Broadcast multicast service Single Frequency Network
MIMO	Multiple-Input Multiple-Output
ML	Machine Learning
MME	Mobility Management Entity
mMTC	massive Machine-Type Communication
MNO	Mobile Network Operator
ng-eNB	Next Generation e-NodeB
NLoS	Non-Line of Sight
NR	New Radio
OFDM	Orthogonal Frequency Division Multiplexing
OFDMA	Orthogonal Frequency-Division Multiple Access
PAPR	Peak-to-Average Power Ratio
PBCH	Physical Broadcast Channel
PCFICH	Physical Control Format Indicator CHannel
PCI	physical cell ID
PDCCH	Physical Downlink Control CHannel
PDN	packet data network
PDSCH	Physical Downlink Shared CHannel
PGW	Packet Data Network Gateway
PHICH	Physical HARQ Indicator CHannel
PN	Pseudo-Noise

PRACH	Physical Random access Channel
PRB	Physical Resource Block
PRS	Performance reporting systems
PS	Packet Switching
PSS	Primary Synchronization Signal
PUCCH	Physical Uplink Control Channel
PUSCH	Physical Uplink Shared Channel
QAM	Quadrature Amplitude Modulation
QoS	quality of service
QPSK	Quadrature Phase Shift Keying
RAN	Radio Access Network
RAT	Radio Access Technology
RB	Resource Block
RE	Resource Element
RF	Radio Frequency
RME	Relative Mean Error
RMSE	Root Mean Square Error
RNN	Recurrent Neural Network
RS	Reference Signal
SSS	Secondary Synchronization Signal
SAE	System Architecture Evolution
SC-FDMA	Single-carrier FDMA
SCS	SubCarrier Spacings
SDL	Supplemental Downlink
SGW	Serving Gateway
SNR	Signal-to-Noise Ratio
SSB	Synchronization Signal Block
SSS	Static Spectrum Sharing
SUE	Spectrum Utilization Efficiency
TCO	Total Cost of Ownership
TDD	time division duplex
TDL	tapped delay line
UE	User Equipment
UPF	User Plane Function

URLLC	Ultra-Reliable Low Latency Communications

Chapter 1

Introduction

Nowadays, the demand for high-speed and reliable wireless communication is increasing exponentially with the emergence of various data-hungry applications [1]. To cater to this challenge, 5G deployment is underway, promising to provide not only high data rates but also a more pervasive and flexible network architecture. 5G NR enables a variety of services, including enhanced Mobile BroadBand (eMBB), Ultra-Reliable Low Latency Communications (URLLC), and massive Machine-Type Communication (mMTC) [2].

Cellular communication has limited spectrum resources, especially in licensed bands where allocation is high. This scarcity of radio spectrum is the main challenge for mobile operators to deploy 5G in the current mobile communication ecosystem[3], [4]. Traditionally, new mobile generations are typically assigned separate frequency bands by mobile operators. Consequently, operators will have to buy or rent new spectrum bands, which is a slow and costly process [4]. The potential solution to this problem will be identifying low spectrum utilization spots in certain networks and utilizing spectrum-sharing technologies efficiently.

Static Spectrum Sharing (SSS), also known as "hard" re-farming, and Dynamic Spectrum Sharing (DSS) are two options for spectrum sharing. These options enable LTE and 5G NR to coexist in low and existing mid-frequency bands that are currently occupied by LTE [5]. The SSS option works by assigning a dedicated carrier for each technology within the same band. Mobile Network Operator s (MNOs) including ethio telecom have been using this technique in earlier generations, from Second Generation (2G) to 4G, to share frequency bands like 800MHz, 900 MHz, 1800 MHz, and 2100 MHz. However, achieving the desired throughput is not possible due to a lack of flexibility in the SSS, considering the traffic dynamics. DSS has been proposed as a solution to allow the flexible allocation of spectrum resources between 4G LTE and 5G NR technologies. It allocates frequencies for LTE and 5G NR based on instantaneous traffic conditions in the cell, ensuring efficient utilization of the spectrum. With DSS it is now possible to simultaneously use 4G LTE and 5G NR in the same frequency band.

DSS between LTE and 5G NR networks presents several challenges, including interference management, quality of service (QoS) guarantee, and spectrum utilization optimization. To ensure efficient DSS allocation, spectrum utilization prediction can play a crucial role. This involves projecting future trends in spectrum usage, which can help optimize the allocation of resources and prevent potential issues such as signal collisions and QoS degradation.

In this thesis work, we conducted a prediction of LTE spectrum utilization at the cell level to enable proactive decision-making of the DSS controller. Additionally, we applied RE-level rate-matching DSS to the prediction results and evaluated the performance of the proposed strategy. We obtained the data from Ethio telecom's Performance reporting systems (PRS) for a specific LTE eNB in Addis Ababa, collected over a period of 124 days. With these results, Ethio telecom, as well as any other operator, will have access to valuable information for frequency planning, sharing, and management. This data will also facilitate the most effective allocation of resources.

1.1 Problem Statement

Nowadays, many operators are deploying 5G networks in order to increase connectivity and meet the rising demand for data services. However, the rollout of 5G has been slower compared to LTE due to various reasons such as its limited coverage range and high Total Cost of Ownership (TCO). One major challenge faced by operators is spectrum scarcity which affects the availability of suitable frequencies for different cases of deployments.

A new mid-band, 3500MHz emerged as a key band for 5G deployment in different countries. This band alone doesn't fulfill 5G criteria. To address various use cases such as coverage, capacity, and quality of services, 5G NR is designed to operate in lower, mid, and higher bands. However, lower bands with favorable coverage are already allocated for previous mobile generations. Exploiting those bands without affecting legacy networks is a difficult challenge for MNO. This problem provides researchers with a new avenue for investigation.

In order to address this challenge, DSS between LTE and 5G NR networks is a promising solution to address the spectrum crunch and improve wireless mobile communication capabilities. DSS allows for the efficient allocation of spectrum resources between LTE and NR technologies based on user demands, thereby improving spectral efficiency levels and overall utilization. By dynamically configuring the physical layer of the network, unused LTE resources can be assigned to support NR signals wherever possible.

The successful implementation of DSS not only enhances connectivity but also optimizes resource allocation across different dimensions within existing allocated spectrums and QoS assurance. However, the success of DSS heavily relies on accurate knowledge of spectrum utilization patterns. ML-based approaches for spectrum utilization prediction can play a crucial role in DSS management and optimize resource distribution.

By employing such innovative approaches, operators can maximize the utilization of available resources while simultaneously supporting both 4G LTE and 5G NR systems on a single dedicated carrier. This ensures optimal spectral efficiency without compromising performance or limiting network capabilities. The key foundation for achieving this seamless coexistence lies in the adaptive configuration of the physical layer in 5G networks, allowing efficient allocation of NR signals within any unused LTE resources whenever possible.

As pointed out priory, QoS assurance in DSS is another critical aspect that needs to be addressed in order to ensure a smooth transition from 4G to 5G. Implementing dynamic spectrum-sharing technology is crucial for addressing the challenges associated with next-generation technology like 5G. Minimizing the impact of DSS on existing network performance and ensuring a consistent QoS for both 4G LTE and 5G NR users is essential. This can be achieved by conducting performance measurements with some constraints like maximum tolerable noise figure, distance between user and eNBs, and SNR. Real-time monitoring and proactive optimization of network parameters are essential to ensure that the network is operating at its full potential.

Overall, DSS is a promising technology that can help operators like Ethio telecom to fully leverage the advantages of 5G and improve the performance of their networks. By studying the spectrum utilization behavior with regard to the temporal and spatial variation of a network, operators can find more efficient and robust spectrum-sharing mechanisms that will ensure seamless business operations and improve coverage, indoor penetration, capacity, and smooth migration. For example, operators can use ML to predict future spectrum utilization and adjust the DSS parameters accordingly. This can help to ensure that the 2600 MHz band is used efficiently and effectively, even in the face of changing traffic patterns.

1.2 Objective

1.2.1 General Objective

This thesis proposes a ML-based, dynamic access-aware resource allocation approach for 5G NR users, which makes use of spectrum utilization prediction techniques derived from LTE network data to enable RE-level rate matching DSS and increase cell capacity.

1.2.2 Specific Objectives

- ☞ Investigate literature based on DSS, spectrum utilization measurement, and prediction.
- ☞ Explore and choose efficient ML algorithms that are suitable for spectrum utilization prediction.
- ☞ Collect data from the Ethio telecom's Element Management Systems (EMSs) and PRSs.
- ☞ Develop, evaluate, and compare different ML models for LTE spectrum utilization prediction.
- ☞ Predict LTE spectrum utilization with respect to time variation.
- ☞ Explore DSS techniques between LTE and NR. Investigate and compare various dynamic spectrum sharing techniques that enable efficient coexistence of LTE and 5G NR networks.

- ☞ Develop an efficient spectrum-sharing strategy. That maximizes the utilization of available spectrum resources while ensuring seamless coexistence between LTE and 5G NR networks.
- ☞ Validate the proposed approach through simulations. Evaluate DSS performance for both Radio Access Technology (RAT) based on ML prediction. Compare the proposed DSS approach with SSS. Assess the performance gains achieved in terms of enhanced cell capacity, improved spectrum utilization, and overall network efficiency.
- ☞ Finally, analyze the result, and draw conclusions and recommendations.

1.3 Literature Review

Researchers have employed various approaches to model spectrum utilization and dynamic spectrum sharing across different generations of cellular networks. These models enable them to effectively plan, manage, and forecast future spectrum utilization in terms of time, frequency, and spatial dimensions. As a result, different technologies can coexist and share a spectrum.

The DSS technique is categorized under learning-based and non-learning-based methods. Due to their dynamic nature, learning-based methods are often more convenient than non-learning methods when it comes to wireless mobile communication. The advantages of learning-based DSS are that it can learn from data in the wireless environment, which can improve spectrum efficiency. It can also adapt to the highly dynamic wireless environment, which can be challenging to model mathematically. Additionally, learning-based DSS can reduce the control overhead in wireless network operations, especially when the number of users is large. By using ML methods, DSS can optimize the spectrum resource allocation and improve the spectrum utilization ratio significantly [6].

The paper [4] aims to improve spectrum efficiency by proposing DSS technology to allocate spectrum dynamically for 4G and 5G users. The paper discusses the interference issues that arise due to the co-frequency interference between the two systems and evaluates the cost of DSS. The methodology includes illustrating the DSS mechanism, introducing mainstream implementation methods, showing actual test results of DSS, and analyzing the performance of 40M DSS in different interference scenarios. The results indicate that the key point of DSS is to develop an efficient interference cancellation method, which should be considered in future DSS deployment. The conclusion suggests that DSS can greatly affect the performance of NR-LTE networks and that an efficient interference cancellation method is crucial for successful DSS deployment.

The paper [7] aims to improve the detection of 4G LTE signals to enable dynamic spectrum access for 5G users. The motivation behind this is the need for efficient and reliable detection of 4G signals for coexistence and sharing of the spectrum between 4G and 5G systems. The proposed methodology involves using ML in the domains of space, time, and frequency for sensing quality improvement. The k-Nearest Neighbors and Random Forest algorithms are used for detection, and simulation results show significant improvement in detection probability. It concludes that the proposed ML-based approach can effectively improve the detection of 4G signals, which is crucial for the successful coexistence and sharing of the spectrum between 4G and 5G systems.

The authors in [8] advocate a solution known as dynamic spectrum refarming (DSR) for deploying LTE small cells using the same spectrum as existing Global System for Mobile Communications (GSM) networks. The main objective is to provide rapid data service to LTE mobile devices while ensuring that the service remains uninterrupted for GSM devices within the same small cell coverage area. The methodology is to deploy LTE small cells in the GSM spectrum but to suppress all signals, including reference signals, in some specific physical resource blocks of a portion of the GSM carriers. This ensures that GSM coverage is maintained. In the study, it is shown that LTE small cells can operate in that spectrum while maintaining normal operation of existing GSM networks. It concludes that Dynamic Spectrum Refarming (DSR) can be an effective solution for reusing the GSM spectrum for LTE small cells.

The paper [9] investigates the impact of DSS for an LTE-NR system, which is a solution for spectrum efficiency where an operator can share the spectrum between two different technologies. The main objective of the work is to analyze the advantages of using DSS technology in an LTE-NR system and propose different schemes for resource allocation in a frame according to the selected sharing ratio. The methodology used in the paper is to evaluate the performance of the LTE-NR system in terms of throughput using the DSS technology and propose different ways for resource allocation for both technologies. The results obtained show that DSS is a good feature for future mobile systems, with an increase in spectrum efficiency and cost reduction. In conclusion, DSS brings advantages to operators from the point of view of spectrum efficiency, cost reduction, and spectrum allocation for 5G systems.

The work [10] presents a proactive dynamic spectrum sharing scheme between 4G and 5G systems using a deep reinforcement learning algorithm based on Monte Carlo Tree Search. The approach predicts future network states by simulating hypothetical bandwidth splits over time. The proposed approach outperforms baseline algorithms and achieves optimal bandwidth splits in various scenarios, including Multimedia Broadcast multicast service Single Frequency Network (MBSFN) subframes, periodic high interference, mixed services, and time multiplexing. It is to exploit deep RL for dynamic spectrum sharing between 4G and 5G systems, improving scheduling efficiency and reducing interference from neighboring cells.

The author of study [11] focuses on the implementation and benefits of DSS in LTE-NR networks. The main objective is to improve spectrum efficiency by introducing various mechanisms for DSS, such as interference mitigation and enhanced scheduling. The paper analyzes the cost of these mechanisms and presents test results for 2.1G DSS. It discusses the development of DSS mechanisms in Third Generation Partnership Project (3GPP), including control channel avoidance, frequency offset, RE-level rate matching, and multiple Cell-specific Reference Signals (CRS) patterns. The paper also introduces DSS enhancement schemes in R16 and R17, such as Type B enhancements and cross-carrier scheduling. The test results highlight the impact of co-frequency interference on DSS performance and emphasize the importance of efficiently avoiding interference.

In general, DSS is the most convenient spectrum-sharing mechanism between 4G LTE and 5G technologies, allowing them to share unused frequencies allocated for LTE networks. Deep learning algorithms are highly recommended for enhancing the performance of DSS by optimizing the distribution of spectrum resources.

1.4 Methodology

The methodology of the research began with a comprehensive literature review to collect information about spectrum measurement, prediction, and dynamic spectrum-sharing techniques. The data set in used was collected from the Ethio telecom LTE performance report system on an hourly basis for 124 days. This data included information about the spectrum utilization of the LTE network over a period of time. The data was collected in a structured format to facilitate preprocessing and analysis.

The collected data was preprocessed to remove any outliers, missing values, or noise. The preprocessing step also included feature engineering to extract relevant features from the raw data. The selected features were used as inputs to the ML models.

Two ML models particularly LSTM and CNN were trained and evaluated using the preprocessed data. The performance of the models was evaluated using standard evaluation metrics such as RMSE, Mean Absolute Error (MAE), and Relative Mean Error (RME).

The model with the best performance was selected based on the evaluation metrics. This model was used to predict the spectrum utilization of the LTE network for future time periods.

The predicted values of the spectrum utilization were used for RE-level rate matching dynamic spectrum sharing technique to evaluate the cell-level performance. The performance of the system was evaluated using standard evaluation metrics such as user throughput and spectral efficiency.

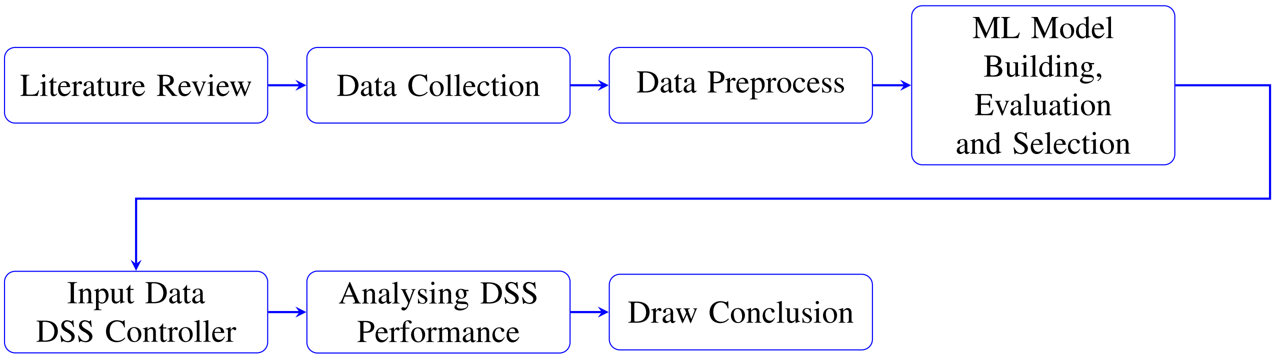


Figure 1.4.1: Block Diagram of Methodology.

1.5 Scope and Limitations

1.5.1 Scope

In this thesis, ML-based models are developed and compared. As a result, the performance of dynamic spectrum sharing is evaluated in terms of user throughput and spectral efficiency at different SNR points. Physical Resource Block (PRB) utilization on the Addis Ababa LTE 2600 MHz network is the only factor considered in the modeling.

1.5.2 Limitation

The physical scope of the research is limited to the spectrum sharing between LTE and 5G NR on the 2600 MHz frequency band of Addis Ababa city. In addition, the effect of interference between LTE and 5G NR signals due to DSS is not covered.

1.6 Contributions

This study will investigate the best ML algorithm for spectrum utilization prediction and potential spectrum-sharing methods to develop a more efficient and robust DSS strategy. As a result, comparatively more reliable DSS methods for LTE and NR will be proposed. Consequently, the main contribution will be:

- ☞ Identify and predict the current and future spectrum utilization of LTE using ML for optimal spectrum sharing and coexistence with 5G NR.
- ☞ Propose a dynamic spectrum sharing mechanism by reusing un-utilized LTE's spectrum resources for 5G NR. This will solve spectrum scarcity for 5G network deployment.
- ☞ It can enable the deployment of 5G in lower frequency bands that are currently occupied by LTE and have good indoor penetration ability.
- ☞ It can significantly lower the deployment cost of 5G NR.
- ☞ It can provide a smooth migration from 4G to 5G NR.

1.7 Thesis Organization

The rest of this paper is organized as follows. Chapter 2 provides an overview of Spectrum allocation, frame structure, and physical channels in LTE and 5G NR, along with a brief description of both technologies. Chapter 3 explains the proposed Dynamic Spectrum Sharing and ML algorithms, including their technical details and practical implementation. Chapter 4 analyzes the simulation results. Lastly, Chapter 5 presents the conclusions and recommendations.

Chapter 2

Overview of Spectrum Usage in 4G LTE and 5G NR

2.1 Introduction

The radio spectrum is used to wirelessly transmit data or information for different services. It is one of the most expensive and strictly regulated national natural resources. The International Telecommunications Union (ITU) is the sole worldwide organization responsible for regulating the shared radio spectrum and orbital resources of the globe by collaborating with national governments [3].

The radio spectrum is divided into different categories to meet various needs such as controlling, range, duplex mode, geographical location, etc. From a control perspective, the radio spectrum is divided into two categories: licensed spectrum and unlicensed spectrum [12]. Licensed spectrum refers to the frequencies that are allocated to specific users or organizations by the government or regulatory bodies. These users have exclusive rights to use the spectrum for their communication needs. Unlicensed spectrum, on the other hand, is open for public use without any exclusive rights. Examples of unlicensed spectrum include Wi-Fi, Bluetooth, etc. By considering duplex mode, it can be classified under the Frequency Division Duplex (FDD) and time division duplex (TDD) spectrums. FDD uses separate frequencies for uplink and downlink communication, while TDD uses the same frequency for both uplink and downlink communication. Also, ITU classifies the spectrum according to geographical location in three regions: Region 1, Region 2, and Region 3. Region 1 includes Europe, Africa, North, and West Asia; Region 2 covers the Americas; and Region 3 covers the rest of Asia and Australia [3].

Spectrum management is the process of ensuring that allocated frequency bands are used efficiently and effectively. It involves monitoring the spectrum utilization in time, frequency, and space dimensions. Time dimension refers to the duration of spectrum usage, frequency dimension refers to the range of frequencies used, and space dimension refers to the geographical area where the spectrum is being used. By monitoring the spectrum utilization in these dimensions, MNOs can identify areas where the spectrum is being underutilized or overutilized and take appropriate actions to optimize its usage.

Overall, a discussion of LTE and 5G NR networks, architectures, spectrum allocation, spectrum sharing, and measurement techniques will be presented in this section.

2.2 LTE Network

LTE is a 4G wireless technology offering high-speed data services with low latency and reliability. It uses Orthogonal Frequency-Division Multiple Access (OFDMA) for downlink transmission and Single-carrier FDMA (SC-FDMA) for uplink, enabling efficient bandwidth utilization for faster connections [13]. OFDMA is a method that enables multiple users to share a frequency band by dividing it into smaller subcarriers. Essentially, it allows users to share the same spectrum in different domains such as frequency, time, code, or phase [14]. This enables efficient utilization of the available bandwidth and allows for faster data transfer rates. SC-FDMA, on the other hand, is a technique that is used for uplink transmission. It is similar to OFDMA but is more suitable for uplink transmission as it requires less power and has a lower Peak-to-Average Power Ratio (PAPR) [13].

Various frequency bands are available for LTE networks, including 700 MHz, 800 MHz, 900 MHz, 1800 MHz, 2100 MHz, and 2600 MHz [15]. As a result of this wide range of frequency bands, network deployment is more flexible, as different bands are optimal for different scenarios. Higher frequency bands, such as 2100 MHz, and 2600 MHz, are better suited for providing high capacity in densely populated areas, while lower frequency bands, such as 700 MHz and 800 MHz, are better suited for providing coverage over large areas.

The LTE standard defines several resource allocation schemes, including FDD and TDD. These schemes allow for efficient use of the available spectrum, which is a limited resource.

2.2.1 4G LTE Architecture

LTE operates on Packet Switching (PS) technology to enable seamless Internet Protocol (IP) networking between the User Equipment (UE) and the packet data network (PDN). A conventional LTE system architecture comprises an Evolved UMTS Terrestrial Radio Access Network (E-UTRAN), and the System Architecture Evolution (SAE). An Evolved Packet Core (EPC), is the primary component of SAE. It is accompanied by SAE which includes the EPC network, making up the Evolved Packet System (EPS) [13]. The LTE SAE does not have a separate network for packet-switched data and circuit-switched voice traffic. Both the data plane and user plane communicate over the same network, which is known as the EPS network.

The E-UTRAN is responsible for the network's radio access. It consists of several base stations known as eNBs that are linked to the EPC. eNBs are responsible for data transmission and reception between UE and the EPC.

The EPC is responsible for the core part of the network. It consists of a number of nodes, including the Mobility Management Entity (MME), the Serving Gateway (SGW), and the Packet

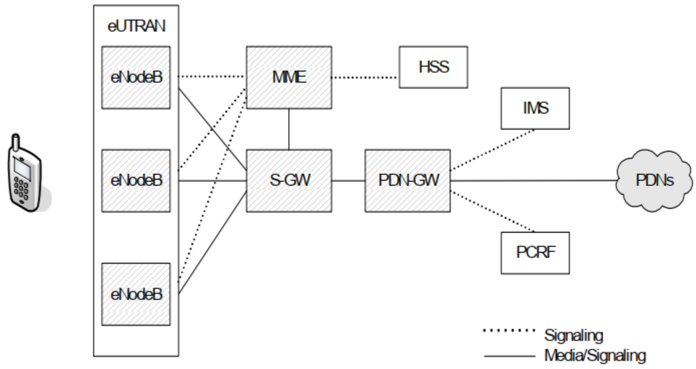


Figure 2.2.1: LTE High-Level Network Architecture [16].

Data Network Gateway (PGW) as depicted in Figure 2.2.1. The MME is responsible for managing the UEs in the network. The SGW is responsible for routing data between the eNBs and the PGW. The PGW is responsible for routing data between the LTE network and the Internet.

2.2.2 Spectrum Allocations for 4G LTE

Spectrum allocation refers to the assignment of specific frequency bands to different wireless communication services or users [17]. It is usually done by regulatory bodies such as the Ethiopian communication authority (ECA) in Ethiopia. Furthermore, it includes careful planning and coordination between different stakeholders such as governments, regulatory bodies, and operators.

The spectrum is divided into frequency bands, each of which has its characteristics and limitations. According to the 3GPP standard, the radio spectrum exploited by the 4G LTE network is between 700 MHz and 2.7 GHz [18]. Currently, out of a total of 65 bands, there are 7, 3, and 2 bands defined for FDD, TDD, and Supplemental Downlink (SDL) respectively for LTE service in Region 1 [15]. To maximize the similarity between the duplex modes, the Radio Frequency (RF) needs for FDD and TDD have been maintained as similar as feasible.

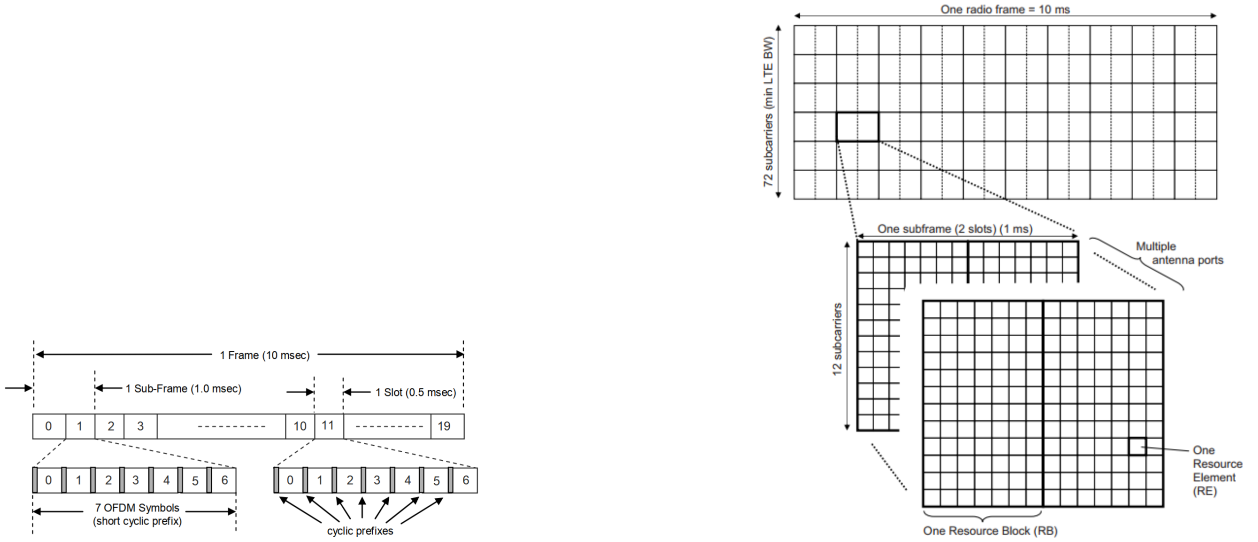
2.2.3 Channel Bandwidth

The LTE channel bandwidth refers to the range of frequencies that are used for transmitting data between the mobile device and the base station. The standard LTE channel bandwidths are 1.4MHz, 3MHz, 5MHz, 10MHz, 15MHz, and 20MHz [18]. It has a significant impact on data rate and the number of users that can be served in a particular area. A larger channel bandwidth allows for a higher data rate, as more data can be transmitted simultaneously. However, a larger channel bandwidth also means that there are fewer available channels, which limits the number of users that can be served in a particular area. Therefore, the choice of channel bandwidth is a trade-off between data rate and the number of users that can be served. In practice, the choice of channel bandwidth depends on various factors such as the available frequency spectrum, the number of users in the area, and the desired data rate.

2.2.4 4G LTE Frame Structure

In LTE, the downlink transmission resources have time, frequency, and space dimensions. At the eNB, a number of ”antenna ports” are used to access the spatial dimension, which is measured in ”layers.” For each antenna port, a Reference Signal (RS) is delivered so that the UE can determine or estimate the radio channel [19].

The transmit antenna ports’ time-frequency resources are divided into ten 1 ms subframes, each with two 0.5 ms slots [20]. For a normal Cyclic Prefix (CP) length, each slot carries seven Orthogonal Frequency Division Multiplexing (OFDM) symbols, or six if an extended CP is enabled. Resources are organized into units of 12 subcarriers in the frequency domain, taking up 180 kHz with a subcarrier spacing of 15 kHz. 12 subcarriers make up a Resource Block (RB), which has a slot duration. The RE, which consists of one subcarrier for the duration of one OFDM signal, is the smallest unit. Figure 2.3.2b shows the resource structure for a typical cyclic prefix length [19].



(a) The Generic Frame Structure of LTE [20].

(b) Basic Time-Frequency Resource Structure of LTE (Normal CP Case [19].

Figure 2.2.2: LTE Frame Structure.

2.2.5 LTE Physical Channels

In the context of LTE channels, physical channels are transmission channels that are responsible for carrying both user data and control messages[19]. User data refers to the actual information that is being transmitted, such as voice or video data, while control messages are used to manage the transmission process itself. Control messages can include information about the quality of the transmission, error correction codes, and other details that help ensure that the data is transmitted accurately and efficiently. These channels are divided into two categories: uplink and downlink channels. The uplink channels are used for transmitting data from the UE to the Base Station (BS), while the downlink channels are used for transmitting data from the BS to the UE.

LTEs’ downlink data and control transporting channels are the Physical Broadcast Channel

(PBCH), Physical Downlink Shared CHannel (PDSCH) , Physical Control Format Indicator CHannel (PCFICH), Physical HARQ Indicator CHannel (PHICH) and the Physical Downlink Control CHannel (PDCCH) [21].

The first channel mentioned is the PBCH, which is responsible for broadcasting system information to all UE in the cell. This channel is transmitted continuously and is modulated using Quadrature Phase Shift Keying (QPSK) modulation. The second channel is the PDSCH, which is used to transmit user data to the UE. This channel is dynamically allocated to different UEs based on their data transmission requirements and is modulated using various modulation schemes such as QPSK, 16 Quadrature Amplitude Modulation (QAM), or 64 QAM [20]. The third channel is the PCFICH, which is used to indicate the number of OFDM symbols used for the PDCCH transmission. This channel is transmitted continuously and is modulated using QPSK modulation. The fourth channel is the PHICH, which is used to indicate the status of the Hybrid Automatic Repeat Request (HARQ) for the PDSCH transmission. This channel is transmitted periodically and is modulated using Binary Phase-shift keying (BPSK) modulation. The fifth and final channel mentioned is the PDCCH, which is used to transmit control information to the UE. This channel is dynamically allocated to different UEs based on their control signaling requirements and is modulated using QPSK modulation [21]. The PDCCH is also responsible for scheduling the PDSCH and PHICH transmissions.

2.2.6 Reference Signals

Reference Signals are signals transmitted by the BS to help the UE estimate the channel characteristics and decode the received data [22]. There are five types of RS in the LTE downlink, called CRSs, UE-specific RSs, MBSFN-specific RSs, Positioning RSs, and Channel State Information (CSI) RSs [19], [23].

LTE uses CRSs to provide a stable and always-on Downlink Reference Signal (DL RS) for various purposes such as synchronization, channel parameter estimation, and demodulation reference [24].

The number of CRS ports and a subcarrier offset are used by the network to configure the CRS transmission. The number of enabled CRS ports determines the available offsets, which are connected to the physical cell ID (PCI) gleaned from the Primary Synchronization Signal (PSS) and Secondary Synchronization Signal (SSS). A Pseudo-Noise (PN)-generated sequence is used to create the QPSK-modulated signal sequence that is used for CRS.

If the eNB is able to transmit more than two layers of PDSCH using a CRS-based transmission scheme, CRS ports 2 and 3 are typically set up to be transmitted. Although these ports have a lower time density than ports 0 and 1, they are not utilized for measurements of mobility and reference signal received power. Since the CRS is present in every DL subframe and spans the whole serviced cell, CRS-based transmission systems provide high channel estimation performance and robustness. Although there is currently no served UE, this ”always on” CRS broadcast causes the base station to use energy. Additionally, even when a cell is not sending any data, interference can still be caused by its CRS if it differs from the serving cell’s CRS in terms of subcarrier offset.

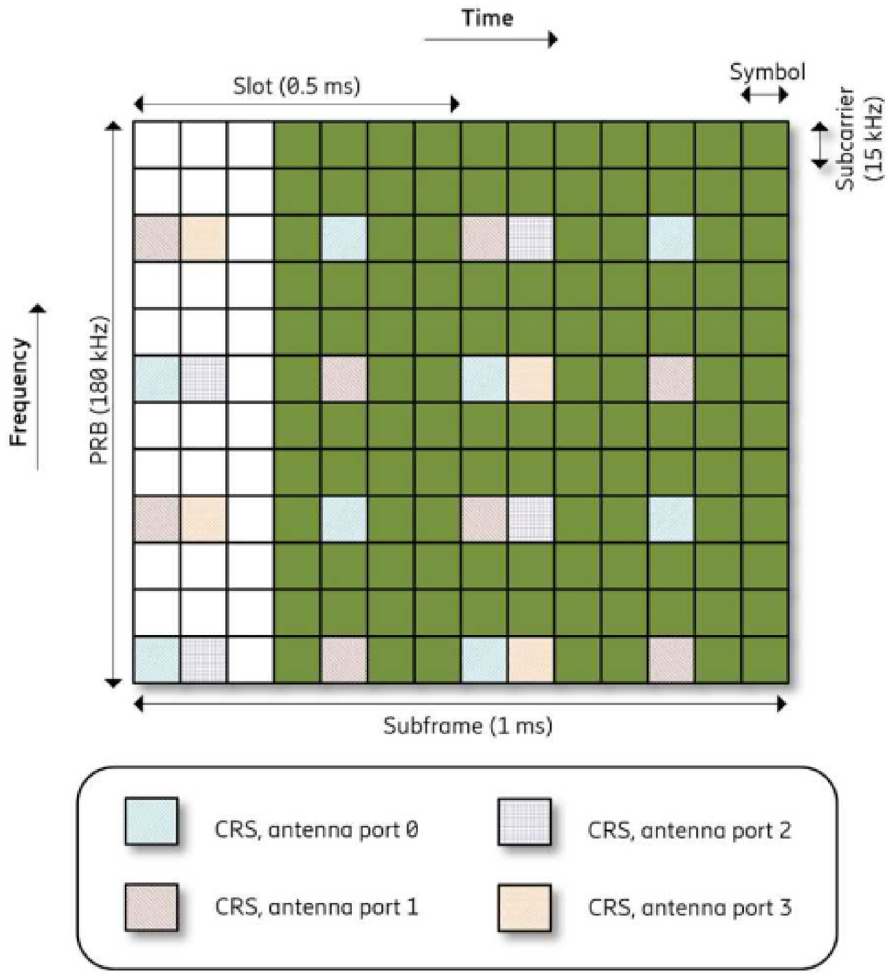


Figure 2.2.3: LTE CRS Mapping to RE in Subframe [24].

In LTE, the number of CRS can vary based on different parameters. One of the parameters that can affect the number of CRS symbols is the number of antenna ports in the cell. Antenna ports are physical interfaces that connect the radio equipment to the antennas. Each antenna port can transmit a separate CRS symbol, which means that the more antenna ports a cell has, the more CRS symbols it can transmit.

2.3 5G Network

Wireless networks of the fifth generation (5G) are known as 5G NR. Our connection to the internet is expected to change significantly as a result of this technology. 5G NR offers faster internet speeds for users due to its higher data rates. It also promises lower latency, which is the time it takes for data to travel from one point to another. Consequently, there will be less delay in data transfer, resulting in a more seamless user experience. 5G NR offers massive connectivity, connecting more devices simultaneously without affecting performance or quality. It upgrades 4G LTE, offering faster download and upload speeds, better video streaming quality, and improved internet performance.

5G NR networks operate in several frequency bands, including sub-6 GHz and millimeter-wave (mmWave) bands[25]. Each frequency band has its unique characteristics, and network operators need to carefully plan and optimize their networks based on the frequency band they are using. The 5G NR standard defines different resource allocation schemes, including FDD and TDD, which can make more efficient use of spectrum resources.

To manage interference and improve spectrum efficiency, 5G NR networks use various techniques such as beamforming, Massive Multiple-Input Multiple-Output (MIMO), and dynamic spectrum sharing. Beamforming is a technique that focuses radio waves in a particular direction to improve signal quality and coverage. Massive MIMO is a technology that uses multiple antennas to enhance the capacity and coverage of the network. Dynamic spectrum sharing (DSS) is a technique that enables the sharing of frequency bands between different cellular technologies, such as LTE and 5G NR, flexibly and efficiently. Additionally, 5G NR networks support various QoS parameters, such as guaranteed bit rate, maximum delay, and minimum throughput. These parameters are crucial for providing a better user experience and ensuring that different types of applications and services are prioritized appropriately.

2.3.1 5G NR Architecture

5G network architecture is designed to support fast and reliable connections And a variety of applications and services that use new concepts to achieve flexible deployment. [25]. The 3GPP has made public both a non-standalone and a standalone network architecture for 5G communications systems [9], [26]. The term ”standalone” (SA) alludes to a 5G network capable of functioning independently from other cellular networks. It essentially indicates that the 5G network does not require assistance from other networks to function. In contrast, a Non-Standalone (NSA) 5G network is built on top of an existing 4G LTE infrastructure. It is demonstrated that the 5G network requires the 4G network for specific duties.

The 5G NR architecture, as per the 3GPP TS 38.300 specification, includes Next Generation Node B (gNB) and Next Generation e-NodeB (ng-eNB) nodes connected to the 5GC via the NG interface, with Access and Mobility management Function (AMF) and User Plane Function (UPF) functions. The specification explains the user plane and control plane of 5G NR, which are two separate parts of the network that handle different types of data and signaling. The user plane protocols are responsible for transmitting user data, such as voice, video, and internet traffic, between the 5G smartphone and the 5G Radio Access Network (RAN). The control plane protocols, on the other hand, handle signaling messages that control the establishment, maintenance, and release of connections between the smartphone and the RAN. The 5G NR RAN architecture includes various interfaces, such as NG, Xn, and F1, which are used for communication between different network elements. The NG interface connects the 5G RAN to the 5G Core Network (5GC), which is responsible for managing the overall network functions. The Xn and F1 interfaces are used for communication between different RAN nodes, such as base stations and small cells, to ensure seamless handover and coordination. The interaction between the 5G smartphone and the 5G RAN takes place over the Uu radio interface, which is a wireless link that uses radio waves to transmit data and signaling messages. The 5G RAN and 5GC interact with each other to ensure efficient network operation and management.

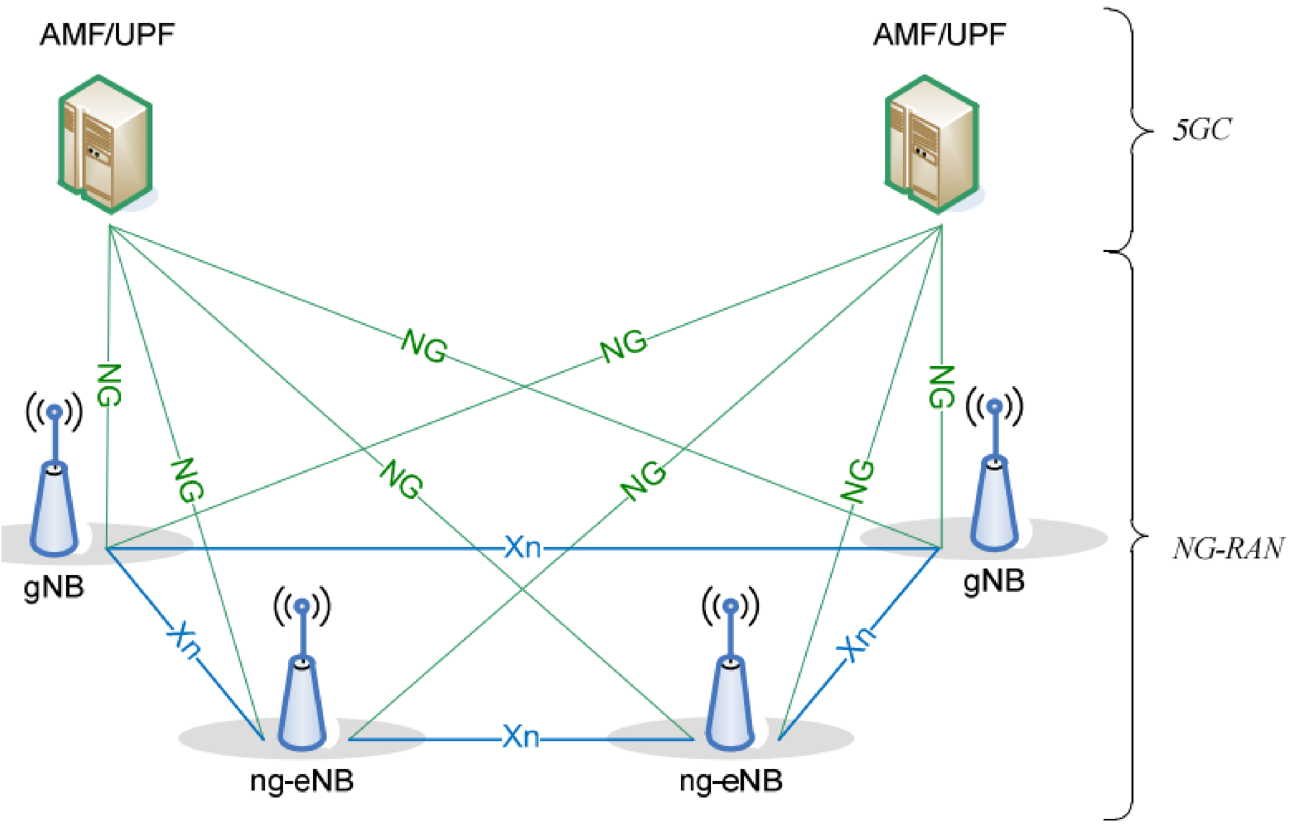


Figure 2.3.1: Overall 5G NR Architecture [27].

2.3.2 Spectrum Allocations for 5G NR

The ITU takes decisions at its World Radiocommunication Conferences (WRCs) every three to four years. Two decisions at WRC-15 were particularly relevant to 5G, such as the assignment of the 3400–3600 MHz band to cellular networks in ITU regions 1 and 2, and the opening up of the 694–790 MHz cellular band. At WRC-19, the ITU identified the bands 24.25–27.5, 37–43.5, 45.5–47, 47.2–48.2 and 66–71 GHz for use by 5G[28].

5G is the first mobile radio technology designed to use any spectrum between 1 GHz and millimeter waves. Additionally, 5G is intended for deployment in licensed, shared, and unlicensed spectrum bands[29]. According to 3GPP technical report [30], the Frequency Ranges (FR) in which 5G NR can operate is described in Table 2.3.1.

Frequency range designation		Corresponding frequency range
FR1		410 MHz – 7125 MHz
FR2	FR2-1	24250 MHz – 52600 MHz
	FR2-2	52600 MHz – 71000 MHz

Table 2.3.1: NR Frequency Range [30].

In order to address 5G NR services, a multi-layer spectrum approach is required [31]. The first layer is called the ”Capacity and Coverage Layer,” which uses a spectrum in the range of 2 to 6 GHz. This layer is designed to provide an optimal balance between capacity and coverage. The second layer is called the ”Super Data Layer,” which employs a spectrum over 6 GHz, such as mmWave. This layer is designed to support use cases that require exceptionally high data rates, such as virtual reality, augmented reality, and ultra-high-definition video streaming. The third layer is called the ”Coverage Layer,” which utilizes a spectrum below 2 GHz, such as 700 MHz. This layer is designed to provide extensive indoor coverage over a vast region, such as a city or a rural area.

The multi-layer spectrum approach is necessary because different use cases have different requirements for data rates, coverage, and capacity. For example, a user who is streaming a high-definition video on a crowded street may require a different spectrum than a user who is making a voice call in a rural area. The use of different spectrum bands also allows for better spectrum utilization, as each band can be optimized for its specific use case. For example, the 2 to 6 GHz band is ideal for providing coverage in urban areas, while the mmWave band is better suited for providing high-speed data in dense areas. The multi-layer spectrum approach is also necessary to ensure that the 5G NR network can support a wide range of use cases, from low-bandwidth IoT devices to high-bandwidth applications like virtual reality.

2.3.3 5G NR Transmission Bandwidth Configuration

The 5G transmission bandwidth can be customized to fulfill the requirements of several applications. According to the 3GPP standard [32], the 5G NR standard supports numerous bandwidth configurations ranging from as low as 5 MHz to as high as 100 MHz in FR-1. The specific bandwidth that is used will depend on the specific application and the environment in which the network is deployed as depicted in table 2.3.2.

For example, a 5G network that is used for mobile broadband applications, such as video streaming and gaming, will typically use a wider bandwidth than a network that is used for machine-to-machine (M2M) communications. This is because mobile broadband applications require more bandwidth to support the high data rates that are needed for these applications.

	Bandwidth														
SCS (kHz)	5 MHz	10 MHz	15 MHz	20 MHz	25 MHz	30 MHz	35 MHz	40 MHz	45 MHz	50 MHz	60 MHz	70 MHz	80 MHz	90 MHz	100 MHz
	N_{RB}	N_{RB}	N_{RB}	N_{RB}	N_{RB}	N_{RB}	N_{RB}	N_{RB}	N_{RB}	N_{RB}	N_{RB}	N_{RB}	N_{RB}	N_{RB}	N_{RB}
15	25	52	79	106	133	160	188	216	242	270	N/A	N/A	N/A	N/A	N/A
30	11	24	38	51	65	78	92	106	119	133	162	189	217	245	273
60	N/A	11	18	24	31	38	44	51	58	65	79	93	107	121	135

Table 2.3.2: Transmission Bandwidth Configuration N_{RB} for FR1 [30].

2.3.4 Numerology

Numerology is a term used to describe the physical layer parameters of an OFDM system. A signal structure is defined by the subcarrier spacing, the symbol duration, and the cyclic prefix length. 5G NR supports multiple different numerology types, which is one of its key differences from LTE. LTE only has one type of subcarrier spacing, which is 15 kHz.

The numerology types in NR are discussed in [33], and the Table 2.3.3 can facilitate a clearer comprehension of these numerology types. Numerology types are labeled with a parameter (μ, mu in

Greek). The numerology (μ = 0) corresponds to the 15 kHz subcarrier spacing, which is the same as the subcarrier spacing of LTE. As shown in the table, other subcarrier spacing values are calculated by scaling up in the power of 2, starting with ($/mu$=0). Using the same procedure, the subcarrier spacing of numerology 4 ($/mu$ = 4) is 15 kHz x 2^4 = 240 kHz. This is a wider subcarrier spacing than LTE, which can be used to support higher data rates.

μ	$\Delta f = 2^{\mu}.15[KHz]$	Cyclic prefix
0	15	Normal
1	30	Normal
2	60	Normal, Extended
3	120	Normal
4	240	Normal

Table 2.3.3: 5G Numerology [33].

The different numerology types in NR offer different trade-offs between bandwidth, spectral efficiency, and power consumption. The choice of numerology will depend on the specific application and the environment in which the network is deployed. For example, a network that is used for mobile broadband applications will typically use a wider subcarrier spacing to support higher data rates. A network that is used for machine-to-machine (M2M) communications will typically use a narrower subcarrier spacing to conserve power.

The numerology is an important parameter that needs to be considered when designing a 5G NR network. The specific values that are used will depend on the specific application and the environment in which the network is deployed.

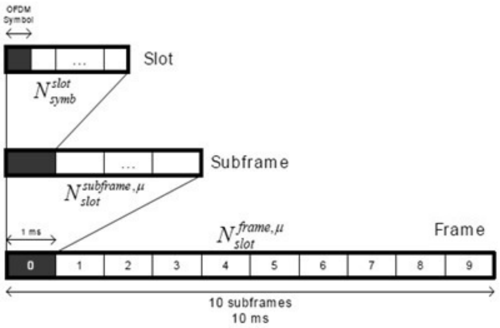
2.3.5 5G NR Frame Structure

The 5G NR Frame Structure refers to the way data is organized and transmitted over the air interface between the base station and the user equipment. It is divided into different time and frequency domains, which are used to carry different types of information such as control signals, user data, and synchronization signals.

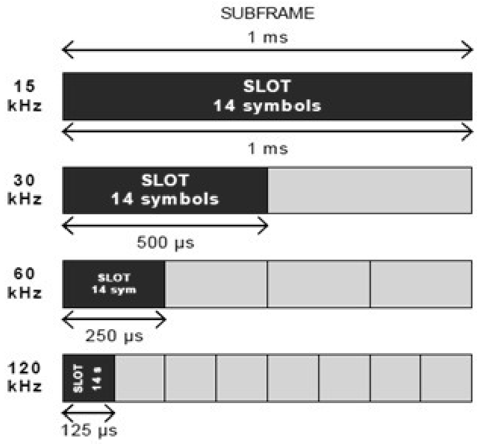
The frame structure is designed to support both TDD and FDD modes of operation, which are used to transmit data in both uplink and downlink directions. It is an essential component of the 5G network architecture, and its efficient design is critical to achieving high data rates, low latency, and reliable connectivity.

A single frame in the system lasts for only 10 milliseconds (ms). This frame is then divided into two halves, with each half containing five subframes. These subframes have a duration of 1 ms, which is comparable to that of the LTE technology. The number of OFDM slots available in the subframes, however, is not fixed but instead varies depending on the numerology used.

It is designed to be flexible and scalable, allowing 5G NR to adapt to different use cases and network conditions. It consists of different types of subframes, each with a specific purpose and duration. Numerology is the basic idea behind all the flexibility.



(a) Frame Structure of 5G NR.



(b) Basic Time-Frequency Resource Structure of LTE (Normal CP Case.

Figure 2.3.2: 5G NR Frame Structure [34].

2.3.6 5G NR Physical Channels

In the 5G network, there are three types of channels, which are similar to those in LTE that are known as logical channels, transport channels, and physical channels. The first type of channel is the Logical Channel, which is responsible for carrying information between the higher layers of the network. These channels are classified into two categories: Control Channels and Traffic Channels. The second type of channel is the Transport Channel, which is responsible for carrying information between the physical layer and the higher layers of the network. These channels are classified into two categories: Dedicated Transport Channels (DTCH) and Common Transport Channels (CTCH) [35].

The main physical channels include PDSCH for unicast data transmission, PBCH for system information, PDCCH for downlink control information, Physical Uplink Shared Channel (PUSCH) for uplink data transmission, Physical Uplink Control Channel (PUCCH) for acknowledgments and channel-state reports, and Physical Random access Channel (PRACH) for random access. These physical channels play important roles in providing necessary information for reception, decoding, scheduling, and transmission in the network [35].

2.4 Spectrum Measurement

Spectrum measurement refers to the process of analyzing and quantifying the frequency distribution of a signal or system. Wireless communication systems rely on spectrum measurements to determine various characteristics like signal strength, bandwidth utilization, and interference levels. It is critical for evaluating system performance and optimizing its efficiency.

There are two key measures of spectrum utilization called absolute measures and relative measures [12], [36]. Absolute measures help spectrum administrators and government managers assess the overall level of spectrum utilization across a wide range of radio services. This kind of measure can either be overly simplified or complex. Relative measures are applied to specific services with established network parameters and are often expressed in terms of system capacity. They are instrumental in guiding system designers to achieve higher Spectrum Utilization Efficiency (SUE). Ethio telecom's PRS measures PRB utilization in percent from traffic volume of LTE network. This data can aid in spectrum sharing between LTE and 5G by providing insights into how many PRBs are currently being used by LTE and how many are available for allocation to 5G.

Chapter 3

The Fundamentals of Machine Learning Algorithms and Dynamic Spectrum Sharing Techniques

3.1 Machine Learning

The goal of machine learning is extracting knowledge from data. It involves training computers to learn from data and make predictions or decisions based on that data. It combines statistics, artificial intelligence, and computer science [37], [38]. Over the past few years, machine-learning techniques have become ubiquitous.

In the early days of ”intelligent” applications, many systems processed data or adapted to user input using hand-coded ”if” and ”else” rules. However, using hand-coded rules has two main limitations or disadvantages when making decisions. The first is the logic applied to make a decision specific to a domain the task is required. The second limitation is design rule requires a deep understanding of the experts[38].

There are three types of machine learning: supervised learning, unsupervised learning, and reinforcement learning.

1. **Supervised Learning:** In supervised learning, an algorithm learns from labeled data. In supervised learning, the correct output is associated with the input data, and the algorithm learns to map the input to the output. The objective of supervised learning is to acquire a function capable of predicting the output of new input data. Supervised learning is represented by the equation[37]:

   $$Y_i = a + BX_i \tag{3.1}$$

   where:

   - X_i is the input,
   - Y_i is the target, and i iterates from 1 to N,

- a is the y-intercept and
- B is the input feature.

2. **Unsupervised Learning:** The second type of machine learning is known as unsupervised learning, in which the algorithm learns from unlabeled data. In this type of machine learning, the input data is not labeled and the algorithm discovers patterns and structure in the data[38]. The objective of unsupervised learning is to discover the fundamental data structure.

3. **Reinforcement learning:** Reinforcement learning is a form of machine learning in which an algorithm learns by trial and error. In reinforcement learning, an algorithm interacts with an environment and learns to maximize a reward signal by taking actions. The objective of reinforcement learning is to discover a strategy that maximizes the cumulative reward over time.

3.1.1 Deep Learning

Deep learning is a subset of artificial intelligence and machine learning that uses neural networks with multiple layers to learn complex data representations. Due to its remarkable ability to handle unstructured large-scale datasets, this technique has received significant attention in recent years. Using unsupervised or semi-supervised methods, Deep Learning can make accurate predictions based on raw data without explicit labeling by humans. The technique has been successfully applied in a variety of fields, including computer vision, natural language processing, speech recognition, and more recently medical image analysis, achieving state-of-the-art results [39]. Also, in the telecommunications sector, it has significant potential applications in dynamic spectrum sharing as well, by enabling accurate prediction of traffic demands and resource allocation.

In the field of deep networks, Architecture has evolved over the past two decades, and new research is ongoing. This work focuses on two of the most important architectures of deep neural networks called Recurrent Neural Networks particularly LSTM, and CNN.

3.1.1.1 Long Short-Term Memory (LSTM)

LSTM is a type of recurrent neural network (RNN) that is specifically designed to learn long-term dependencies. This is in contrast to traditional RNNs, which can struggle to learn long-term dependencies due to the vanishing gradient problem [37]. LSTMs overcome this problem by using a gating mechanism that allows them to control the flow of information through the network.

LSTMs have been shown to be very effective for a variety of tasks, including natural language processing, speech recognition, and time series forecasting. In the context of time series forecasting, LSTMs can be used to predict future values of a time series based on its past values. This can be useful for a variety of applications, such as financial forecasting, demand forecasting, and traffic forecasting.

Before training a supervised learning model such as an LSTM on time series data, the data must be prepared in a specific way. This can involve steps such as feature extraction, normalization, and splitting the data into training, validation, and test sets [40].

The specific steps involved in preparing time series data for LSTM training will vary depending on the specific application. However, the general principles outlined above will apply in most cases.

3.1.1.1.1 Long Short-Term Memory (LSTM) Architecture

At a high level, LSTM operates similarly to an Recurrent Neural Network (RNN) cell. As depicted in Figure 3.1.1, the LSTM consists of three main sections called input, forget, and output.

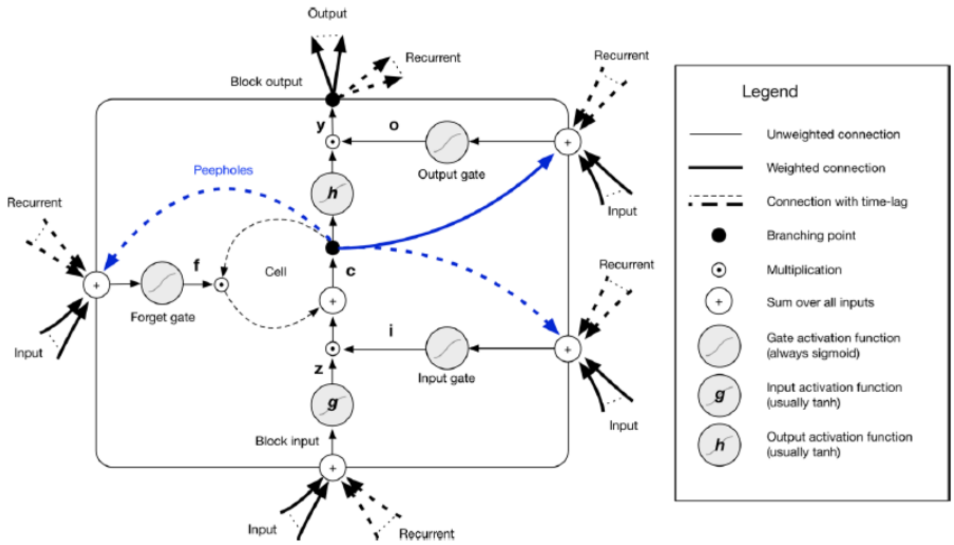


Figure 3.1.1: LSTM Block Diagram [37].

The forget section determines whether information from the previous timestamp should be remembered or discarded as irrelevant. In the input portion, the cell attempts to acquire new information from the data entered into it. In the output section, the cell transmits the updated data from the present timestamp to the following timestamp[37].

Due to limited availability and the high cost of radio spectrum, wireless communication requires efficient spectrum management to maximize its use. Therefore, time series problems like dynamic spectrum sharing require advanced technology to capture temporal relationships between different frequencies and predict future usage patterns accurately. With sophisticated capabilities, such as capturing changes over time and correlating events with sequential data points, LSTMs can enhance collaboration between various technologies for dynamic spectrum-sharing applications effectively. By using LSTMs' predictive analytics functions at scale across multiple devices or endpoints in real-time scenarios beyond fixed-line access networks increases operational efficiency significantly while reducing costs related to capital expenditures on new equipment upgrades or increased capacity demands from end-users or consumers seeking faster internet speeds without compromising their experience quality-wise thanks largely being driven by advancements made possible via AI-powered platforms designed specifically toward addressing these types issues head-on before they become more significant challenges down the road if left unaddressed indefinitely otherwise.

3.1.1.2 Convolutional Neural Network (CNN)

CNN are a type of neural network architecture that is specifically designed for image classification problems. They are inspired by the structure of the visual cortex in the human brain and are designed to automatically learn and extract features from images. Besides image recognition, convolutional neural networks have a wide range of applications. In addition, it can be applied to face recognition, time series data analysis, text recognition, and other areas [41].

Time series forecasting problems can be solved using CNNs' ability to learn and autonomously derive features from unprocessed input data. A sequence of observations can be represented as a one-dimensional (1D) image that a CNN model can read and extract the most salient features from [40].

3.1.1.2.1 Convolutional Neural Networks (CNN) Architecture

The basic structure of a CNN consists of convolutional layers, pooling layers, and fully connected layers. Convolutional layers apply filters to the input image to extract features, pooling layers reduce the spatial size of the output from the convolutional layers, and fully connected layers classify the image based on the extracted features. A CNN 1D convolution is used to extract temporal dimen-

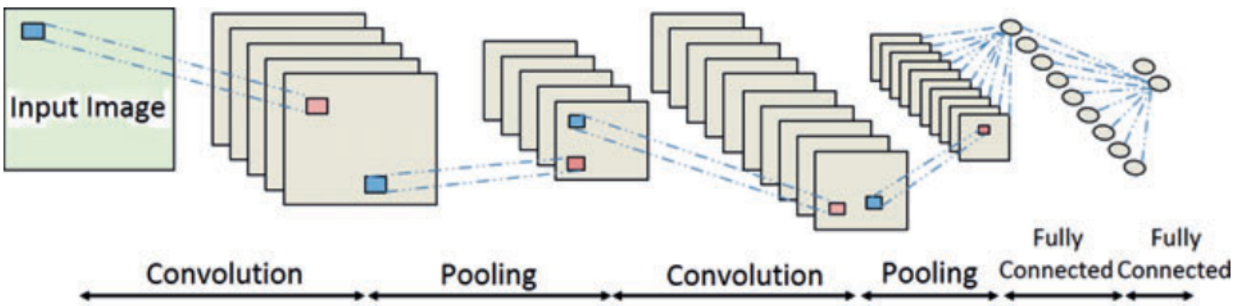


Figure 3.1.2: Architecture of CNN Algorithm [42].

sion information. The convolution can be viewed as a filter applied to a time series and slid over it. In contrast to images, filters have only one dimension which is a time dimension, not two (width and height). Alternatively, the filter can be a universal nonlinear transformation applied to a time series [12].

3.1.1.3 Hyperparameters in Deep Learning

In the realm of deep learning, hyperparameters are the configurable settings that determine the behavior and performance of a neural network model [12]. These settings, which include learning rate, batch size, number of epochs, number of layers and neurons, activation functions, regularization techniques, and optimizer type, impact the network's learning process and final accuracy. Their details are discussed below.

Learning Rate: often denoted as α is one of the most critical hyperparameters in deep learning. It minimizes the loss function during training by controlling the magnitude of weight updates. Model performance would suffer if the learning rate was either too low or too high. When the learning rate is low, the network's weights are updated very slowly, which slows down the training process. When the learning rate is large, however, the error starts to diverge [43].

Batch Size: represented as β. It refers to the number of training examples used in a single forward and backward pass during the optimization process. In order to optimize memory utilization, it is important to strike a balance between a larger batch size and a smaller batch size based on the available resources. A larger batch size can lead to faster convergence, but can also require more memory [42].

Number of Layers and Neurons/Hidden Units: in a neural network is another set of hyperparameters that significantly impacts the model's performance. The number of layers determines the depth of the network, allowing it to capture more complex patterns and features from the input data. Oftentimes, the under-fitting caused by having too few hidden units results in excessive training errors. Less training errors will occur due to over-fitting if there are too many hidden units. The quantity of input training instances determines the size of the hidden units [12].

Activation Functions: are mathematical functions applied to the output of neurons in the neural network, introducing non-linearity and enabling the network to learn complex patterns. It determines whether or not the information that the neuron receives is relevant. It converts the input data into a non-linear form before sending it as input to the preceding layer [42].

Regularization Techniques: Regularization techniques, such as L1 and L2 regularization, dropout, and early stopping, are hyperparameters that can help prevent overfitting in neural networks. It ultimately improves the model's generalization capability [44].

Optimizer Types: is another important hyperparameters in ML. It determines the algorithm used to update the model's weights and biases during the training process [45]. Stochastic Gradient Descent (SGD), Adam, RMSprop, Adagrad, etc. are some examples of popular optimizer types. The training of the model may be sped up or slowed down depending on the kind of optimizer used.

Number of Epochs: A number of epochs refers to how many times your model has been trained. Too few epochs can result in underfitting, whereas too many can lead to overfitting [46].

3.1.1.4 Tuning of Hyperparameters

The process of determining the optimal values for the hyperparameters of a machine learning model is known as hyperparameter tuning or optimization. It can be utilized to enhance the performance of the model [45]. There are a variety of methods and techniques for hyperparameter optimization. Some approaches are discussed below.

Grid Search: The Grid Search method is a straightforward and thorough approach to finding the optimal set of hyperparameters. It involves specifying a pre-defined set of hyperparameter values, and then training and evaluating the model for all possible combinations of these values. The combination that produces the best performance is then selected as the optimal set of hyperparameters[45], [47].

Random Search: is an efficient alternative to Grid Search. Instead of evaluating all possible combinations of hyperparameter values, Random Search randomly samples a subset of the hyperparameter space. This approach can be more effective when the hyperparameter space is large and not all hyperparameters are equally important[47].

Bayesian Optimization is a sophisticated method that utilizes probabilistic models to establish a relationship between hyperparameters and a model's performance. The process involves iterative evaluation of the model with different hyperparameter sets, updating the probabilistic model, and selecting the next set of hyperparameters to evaluate based on the updated model. This approach can be more efficient in terms of the number of evaluations required to identify the optimal set of hyperparameters [47].

The choice of method is determined by variables such as the amount of the hyperparameter space, the availability of computational resources, and the particular characteristics of the problem and the model being employed. It is important to note that hyperparameter optimization can be a computationally intensive process, as it frequently requires repeated model training and evaluation. Nonetheless, determining the optimal set of hyperparameters can substantially enhance the performance of a ML model and contribute to improved outcomes.

3.1.1.5 Model Evaluation Metrics

In machine learning, model evaluation metrics are used to quantify the efficacy of a trained model. There are several evaluation metrics available, and the choice of metric depends on the type of problem being addressed (classification or regression) and the task's particular requirements. To assess the efficiency of the proposed model, we employ three performance indices: the mean absolute error (MAE), the mean relative error (MRE), and the root mean square error (RMSE). They are specified by the following equation.

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |f_i - \hat{f}_i| \tag{3.2}$$

$$MRE = \frac{1}{n}\sum_{i=1}^{n} \frac{|f_i - \hat{f}_i|}{f_i} \tag{3.3}$$

$$RMSE = \left[\frac{1}{n}\sum_{i=1}^{n} (f_i - f_i)^2\right]^{\frac{1}{2}} \tag{3.4}$$

where f_i, and $\hat{f}_i$ are the observed value and the predicted value respectively, and n is the number of data points [48].

3.2 The Dynamic Spectrum Sharing Technical Framework

5G NR networks have emerged as promising solutions to addressing spectrum constraints and enhancing wireless communication capability. The need for high-speed and reliable wireless communication is escalating with the advent of data-hungry applications, yet current wireless systems are challenged to meet this demand due to the limited availability of spectrum resources.

3GPP proposed in September 2016 that the NR RAT should support flexible resource allocation between 5G NR and LTE operating in the same block of spectrum (with possible bandwidth overlap) [4]. The deployment of NR is expected to cover a wide range of spectrums, from low-frequency bands (below 6GHz) to new mmWave spectrum (above 6GHz). For early sub 6GHz 5G deployments, it is highly likely that both 5G and LTE will need to be deployed in the same or overlapping spectrum. Dynamic spectrum sharing between LTE and NR is a technical solution that can address the requirements of such deployments [49].

In wireless communication systems, DSS improves spectrum utilization efficiency. It is a concept where spectrum resources are shared among multiple users, devices, or services dynamically, based on their specific needs. DSS allows for the efficient use of spectrum resources by allowing LTE and 5G NR networks to share the same frequency bands.

With the use of numerous numerologies, NR provides a scalable and flexible physical layer design. Based on the band allocated, multiple SubCarrier Spacings (SCS) exist for data channels and synchronization channels.

3.2.1 Options for Dynamic Spectrum Sharing Deployment

DSS is designed to schedule NR users in LTE subframes while avoiding possible collisions with LTE CRS. It also considers the options to fit 5G NR reference signals within the subframes to avoid affecting NR downlink measurements and synchronization[50].

Based on the aforementioned concepts, the two primary deployment options used by vendors today are MBSFN subframe and non-MBSFN or rate matching.

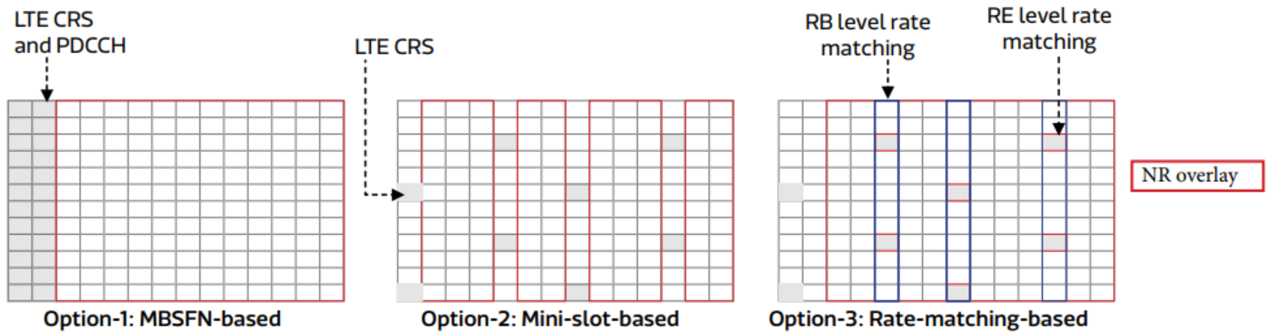


Figure 3.2.1: DSS Deployment Options [50].

3.2.1.1 MBSFN Subframe Based Dynamic Spectrum Sharing

MBSFN stands for Multimedia Broadcast Multicast Service Single Frequency Network. It is a broadcast/multicast transmission technique used in LTE networks to efficiently deliver multimedia content to multiple users simultaneously. In the context of [50], MBSFN subframes are discussed as a possible option for implementing DSS to enable the coexistence of 5G NR and 4G LTE. Despite its effectiveness, there are a few potential limitations such as fixed structure, limited availability, limitations on scheduling, and interference avoidance. The LTE standard stipulates that not all subframes can be used for MBSFN; it cannot be used in certain subframes, for instance, subframe 0/4/5/9 as it contains synchronous signal and paging channel [51].

3.2.1.2 Non-MBSFN Subframe based Dynamic Spectrum Sharing

Non-MBSFN Subframe-based DSS is another DSS technique for enabling the coexistence of 5G NR and 4G LTE. It involves using the non-MBSFN subframes in LTE networks to transmit 5G NR signals, which requires more complex resource allocation and interference management compared to MBSFN-based DSS [50].

Two options for dealing with non-MBSFN subframes containing LTE reference signals are mini-slot scheduling and CRS rate matching. Mini-slot scheduling is not suitable for eMBB applications but can be used for special cases like 30 kHz Synchronization Signal Block (SSB) insertion. CRS rate matching is expected to be the most commonly used option for NR data channels and can be implemented at RB or RE level as depicted in Figure 3.2.1 and 3.2.2.

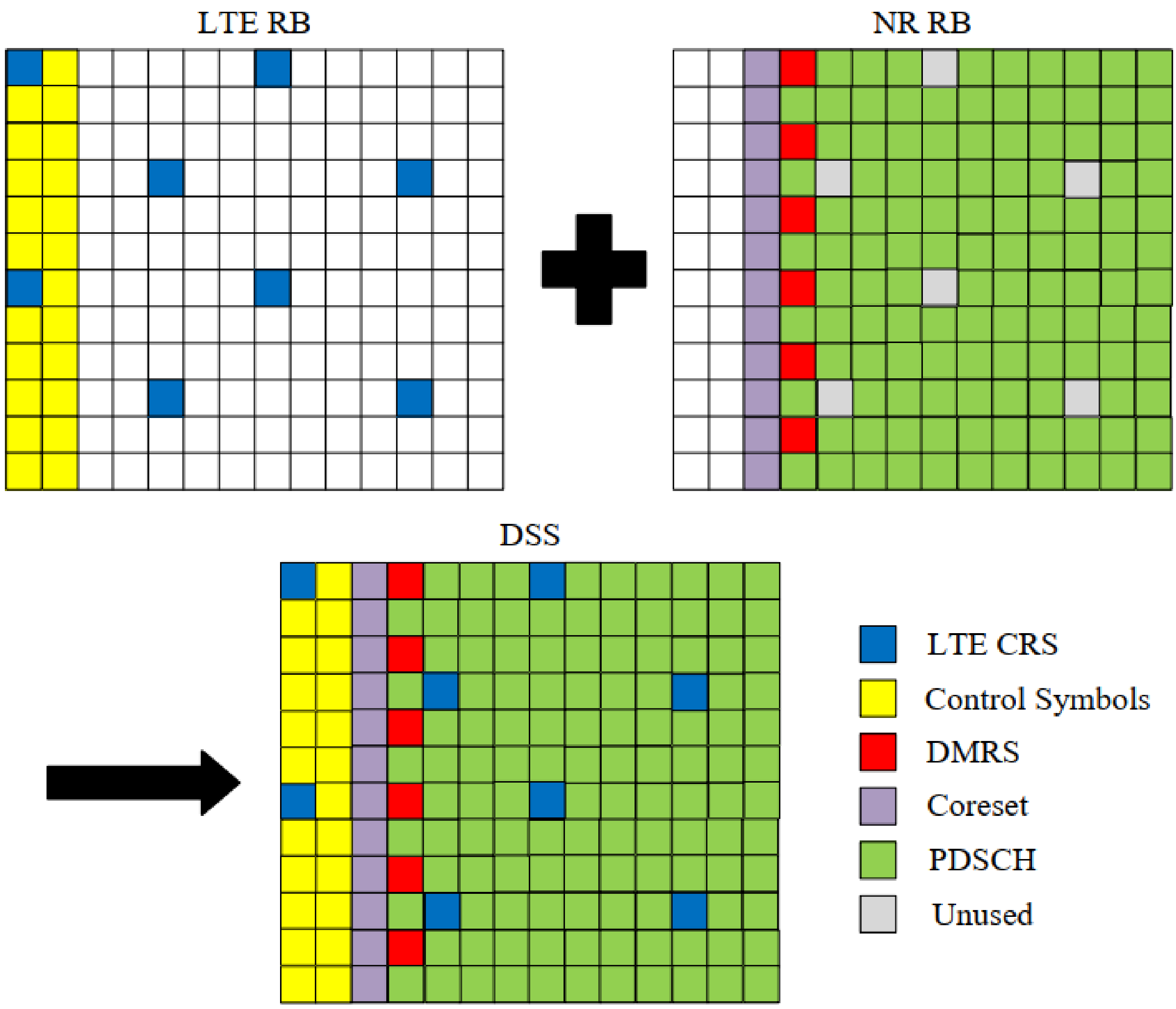


Figure 3.2.2: Rate Matching Schematic Diagram [52].

LTE CRS configuration affects the number of REs available for NR PDSCH in a slot. The available REs per RB depends on the number of CRS antenna ports and whether the RB is muted. LTE CRS occupies four symbols (#0, 4, 7, 11) for one or two antenna ports and two additional symbols (#1, #8) for four CRS antenna ports within an RB [50], [51]. Each CRS symbol consists of two subcarriers for each antenna port, but the first two symbols are occupied by LTE PDCCH and are not considered for rate matching overhead of the NR PDSCH. The overall overhead from CRS to available NR PDSCH symbols becomes 3 CRS symbols * 2 subcarriers = 6 RE for one antenna port, 3 CRS symbols * 4 subcarriers = 12 RE for two antenna ports, and 4 CRS symbols * 4 subcarriers = 16 RE for four antenna ports. NR PDSCH scheduling can only occur after the second symbol in the slot where the third symbol is occupied for NR PDCCH, and as a result, NR PDSCH is scheduled with 11 symbols out of the total 14 symbols available in a slot. Then, 12 RE * 11 Symbols results in 132 RE available in a slot for NR PDSCH. In the case of one LTE CRS antenna port, the total available NR PDSCH REs available in a slot per one RB is 132-6 = 126 REs, 132-12 = 120 REs with two CRS antenna ports, and 132-16 = 116 REs with four CRS antenna ports. If the entire RB in a slot is being muted, 3 (one and two CRS ports) and 4 (otherwise) symbols will be rate matched, resulting in 12 RE per RB *(11 symbols available for PDSCH – 3 CRS symbols muted within NR slot) = 96 REs available for NR PDSCH with one or two CRS antenna ports, and 12 RE per RB *(11 symbols available for PDSCH – 4 CRS symbols muted within NR slot) = 84 REs available for NR PDSCH with four CRS antenna ports. This means that the transport block size for NR PDSCH will be higher in RE rate matching, resulting in better spectral efficiency.

3.2.2 Puncturing

Puncturing is a technique used in wireless communication to handle signal conflicts in overlapping frequency domains. When a signal from one technology (like LTE) conflicts with a signal from another technology (like NR or 5G), the conflicting parts of the signal can be 'punctured' or omitted to avoid interference. There can be LTE CRS puncturing and NR SSB puncturing based on which signal is being manipulated [51], [53].

3.2.2.1 LTE CRS Puncturing

One possible approach to address the issue of LTE CRS interference with NR signal in 5G networks is to employ a technique known as CRS puncturing. This method involves selectively disabling certain LTE CRS transmissions in order to reduce the likelihood of signal degradation or disruption. By implementing this approach, network operators can help ensure that their 5G infrastructure is capable of reliably providing high-quality communication services to end-users.

In this scenario, the LTE side performs CRS power reduction on the RE corresponding to NR public scheduling such as SSB, RMSI, paging, msg2, msg4, etc [53]. The technique can negatively influence channel capacity, measurement accuracy, and the ability to demodulate the signal properly because some part of the signal gets neglected or 'punctured' [51].

3.2.2.2 NR SSB Puncturing

In the context of wireless communication networks, NR SSB puncturing is a technique that serves a similar purpose as LTE CRS puncturing. Specifically, NR SSB puncturing is applied in situations where there is interference between NR SSB and LTE signals. This technique helps to mitigate the negative effects of such interference and ensures that communication is as reliable and efficient as possible. In this case, it is the NR base station that performs the 'puncturing' - actively omitting or neglecting parts of the NR signal that coincide with important parts of the LTE signal. This is usually done at the RE of LTE CRS [51]. By doing this, the interference between NR's SSB and LTE's CRS can be minimized, which helps ensure effective demodulation and functionality of both signals. Yet, puncturing can introduce minor channel capacity and measurement losses.

3.3 Channel Models for Link-Level Evaluations

Channel modeling refers to the process of creating mathematical models that simulate the behavior of wireless communication channels.

3GPP is a global organization that develops standards for mobile communication technologies, and the [54] suggests that some other groups and projects are also involved in channel modeling work. A list of some of these groups and projects, which includes METIS, MiWEBA, ITU-R M, COST2100, IEEE 802.11, NYU WIRELESS, and Fraunhofer HHI.

3.3.1 Clustered Delayed Line (CDL) Models

CDL models are defined for a frequency range of 0.5 GHz to 100 GHz with a maximum bandwidth of 2 GHz. These models can be implemented through coefficient generation or by generating a tapped delay line (TDL) model using a spatial filter. There are five different CDL models, namely CDL-A, CDL-B, CDL-C, CDL-D, and CDL-E, which represent different channel profiles for Non-Line of Sight (NLoS) and Line of Sight (LoS) [54].

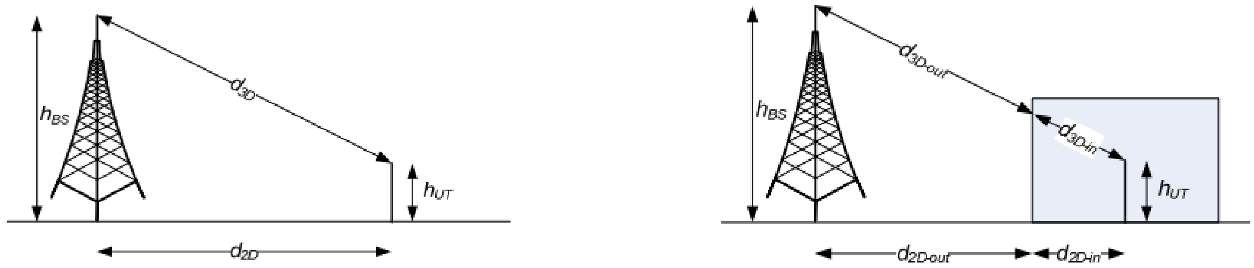
These models evaluate the performance of wireless communication systems by simulating the propagation of radio waves through different environments. The CDL models are particularly useful for evaluating the performance of 5G and other high-frequency wireless systems.

3.3.2 Pathloss

Electromagnetic waves suffer from pathloss as they propagate through space due to a reduction in their power density. In wireless communication systems, pathloss is a critical factor that affects the quality and reliability of the signal.

$$d_{3D-out} + d_{3D-in} = \sqrt{(d_{2D-out} + d_{2D-in})^2 + (h_{BS} - h_{UT})^2} \tag{3.5}$$

$$P_L = 13.54 + 39.08 log_{10}^{(d_{3D})} + 20 log_{10}(f_c) - 0.6(h_u t - 1.5) \tag{3.6}$$



(a) Distance Definition for Outdoor

(b) Distance Definition for Indoor

Figure 3.3.1: Distance Definition in Pathloss [54].

where P_L is the path loss (in dB), d_{3D} is the distance between the UE and BS in 3D space (in meters), f_c is the carrier frequency (in GHz), and h_{ut} is the height of the UE above the surrounding buildings (in meters).

3.3.3 Cell Level Capacity

Cell capacity in a cellular network like LTE and 5G NR refers to the maximum amount of data that can be transmitted within a given cell area at a given time. It is often based on spectrum efficiency and is crucial as it directly influences the speed and quality of data transmission. There are several parameters that can be used to measure cell level capacity, including throughput, and spectral efficiency [55].

In a LTE or 5G NR network, throughput refers to the amount of data sent or received per unit of time by the UE or the BS. It is a quantifier of the network's performance or service quality. The Adaptive Coding and Modulation (ACM) scheme determines the throughput based on available Channel State Information (CSI) [56]. The capacity can also be affected by a number of factors, such as the bandwidth of the channel and the SNR (represented by Shannon's equation 3.7).

$$Thr_{n,m} = B.log_2(1 + SNR_{n,m}) \tag{3.7}$$

where Thr is throughput is the maximum achievable data rate (in bits per second) of the UE-BS link, n, and m are the number of allocated PRB and user, B is the bandwidth (in Hz), and SNR n,m is the signal-to-noise ratio of the UE-BS link (in dB).

$$SNR_{n,m} = \frac{P_t G_t G_r}{P_l N_0 B} \tag{3.8}$$

$$N_0 = \sqrt{\frac{1}{2} K B T_e} \tag{3.9}$$

$$T_e = T_{Ant} + 290 * (NF - 1) \tag{3.10}$$

where SNRn,m is the signal-to-noise ratio of the UE-BS link (in dB), Pt is the transmit power of the

BS/RAT to the UE on a specific RB (in dBm), Gt is the antenna gain at the BS/RAT (in dBi), Gr is the antenna gain at the UE (in dBi), Pl is the path loss between the UE and BS/RAT (in dB), N0 is the noise power spectral density (in dBm/Hz), B is the bandwidth (in Hz), KB is Boltzmann's constant, Te is the equivalent temperature (in Kelvin), T_{Ant} is the antenna temperature at the UE or BS/RAT (in Kelvin), and NF is the noise figure of the UE or BS/RAT.

Spectral efficiency (SE) refers to how efficiently the available spectrum is utilized to transmit data in a wireless network. The higher the spectral efficiency, the higher the data rates that can be achieved within a given bandwidth. It is measured in terms of bits per second per hertz (bps/Hz). LTE and 5G NR aim to achieve higher data rates by maximizing cell capacity through efficient spectrum utilization. According to [57], the spectral efficiency formula for 5G NR is:

$$\mathrm{SE} = \frac{\text{Throughput}}{\text{Bandwidth} \times \text{Resource Utilization}} \tag{3.11}$$

Achieving higher cell capacities is essential for meeting the increasing demand for data transmission and higher data rates, especially under conditions where radio resources are becoming increasingly scarce.

Chapter 4

Results and Discussion

4.1 System Model

The machine learning model is expected to operate on top of the DSS controller to predict the future spectrum utilization of the LTE network. This will enable the controller to optimally distribute spectrum resources for LTE and 5G NR radio access technologies. Two models have been developed using LSTM and CNN algorithms. The best-fit model is proposed to operate with the RE-level rate-matching DSS technique. The performance of the developed strategy is compared with SSS performance to evaluate any compromised performance.

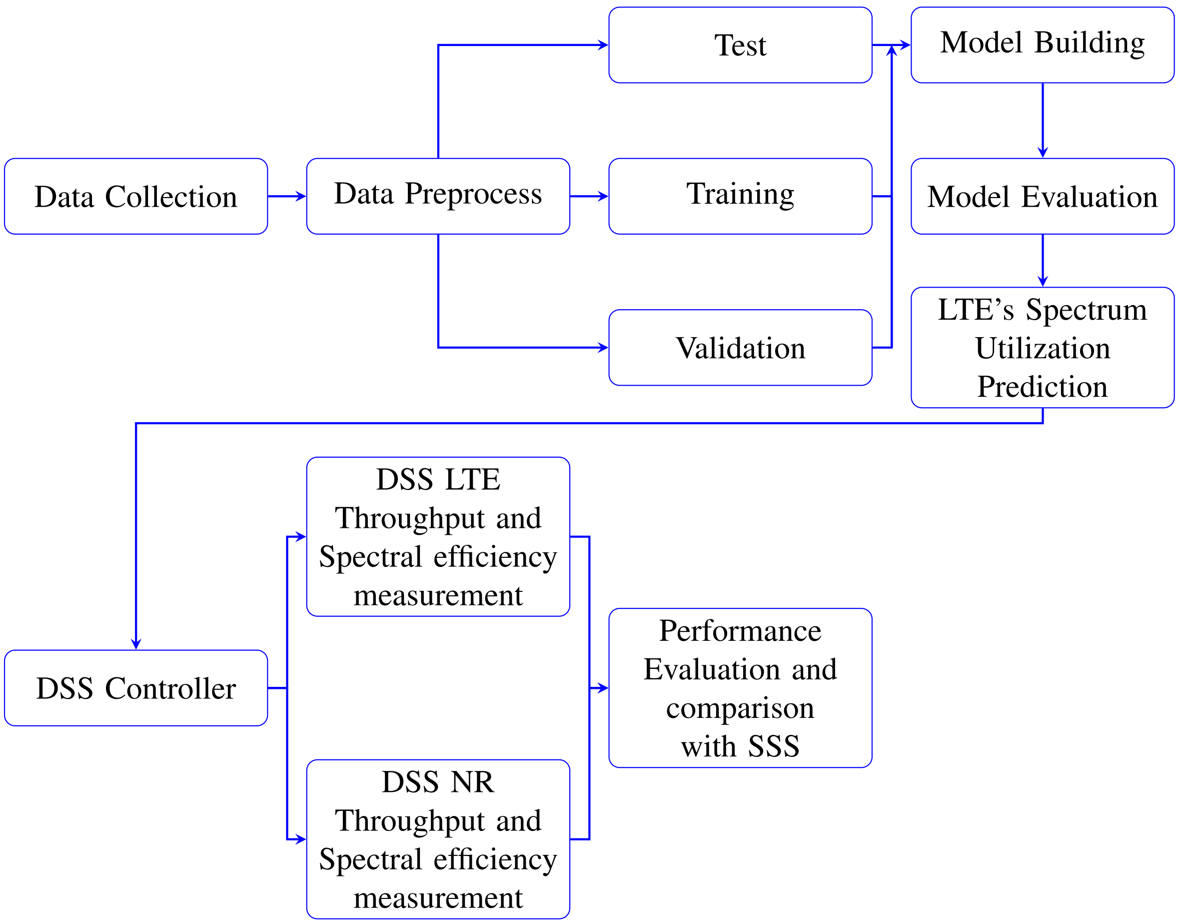


Figure 4.1.1: System Model.

4.2 Description and Pre-processing of the Data

This work focuses on the spectrum resource utilization, particularly PRB utilization, of LTE 2600 MHz (i.e., band 7 with 20MHz bandwidth) at a site in Addis Ababa city. The study leverages a comprehensive data set collected from Ethio telecom's PRS over a period of five months, from January 1, 2023, to May 7, 2023. This data set includes hourly aggregate time series data, which provides a granular view of the site's performance and utilization patterns.

Date Time	DL PRB Utilization (%)
2023-01-04 00:00:00	26.2414
2023-01-04 01:00:00	8.2856
2023-01-04 02:00:00	4.091
2023-01-04 03:00:00	2.2416
2023-01-04 04:00:00	5.323
2023-01-04 05:00:00	10.7776
2023-01-04 06:00:00	19.0853
2023-01-04 07:00:00	10.9085
2023-01-04 08:00:00	10.2045

Table 4.2.1: Sample Data of in-used Data-Set.

4.2.1 Data Pre-processing

It is important to note that the process of treating outliers and missing values is crucial to ensure the accuracy of the analysis. By removing outliers and imputing missing values, we can obtain a cleaner and more accurate dataset for model building and analysis.

The first action taken was to treat outliers. Outliers due to holidays were detected and treated using the interquartile range technique. In addition, due to a power outage and for some unknown reason, five different data points in the dataset contained null values. These missing values were treated by using the median value of the day.

As shown in Figure 4.2.1, the dataset is divided into three parts for model building: training, testing, and validation. The split is done with a ratio of 80%, 10%, and 10%, respectively. Training, testing, and validation dataset were used to build the model, evaluate its performance and test its generalization ability.

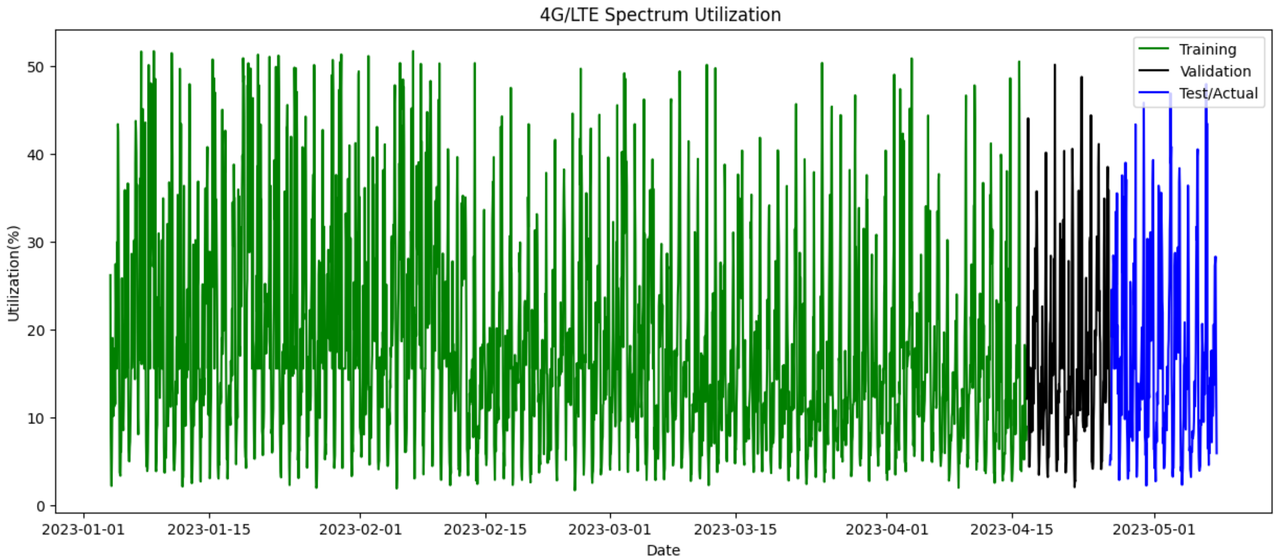


Figure 4.2.1: Pre-processed Data-Set.

4.3 Machine Learning-based Spectrum Utilization Modeling

4.3.1 LSTM Modeling for Spectrum utilization

In the process of developing machine learning models, it is crucial to select optimal hyperparameters. Hyper-parameters are parameters that are set before the training process begins and can affect the performance of the model. Some common hyperparameters for LSTM models include the number of LSTM layers, the number of hidden units in each layer, the learning rate, the batch size, and the number of epochs. These hyper-parameters can be tuned to optimize the performance of the model [58].

Regularization is a technique used in machine learning to prevent the overfitting of models. It involves adding a penalty term to the loss function during training to discourage the model from fitting the training data too closely. In the context of LSTM models, regularization can be applied to the recurrent connections or the attention mechanism to prevent overfitting and improve generalization. Dropout is a well-known regularization technique used in deep learning to prevent the overfitting of models. It involves randomly dropping out (i.e., setting to zero) some of the neurons in a layer during training, which forces the remaining neurons to learn more robust and diverse representations.

In this work, using the grid search algorithm, the best combination of hyperparameters was selected. The model is meticulously constructed by leveraging the carefully selected and optimized hyperparameters, as illustrated in the comprehensive Table 4.3.1. These hyperparameters have been fine-tuned to ensure optimal performance and accuracy in the model's predictions. The results of this highly sophisticated and refined model can be vividly visualized through the captivating depiction presented in Figure 4.3.1, providing a clear representation of its predictive capabilities.

Hyperparameters	Values
Hidden Layer	5
Number of Neurons	250
Bach Size	32
Dropout	0.20%
Optimizer	Adam
Activation	ReLU
Epoch	1000

Table 4.3.1: Simulation Parameters for the LSTM Framework.

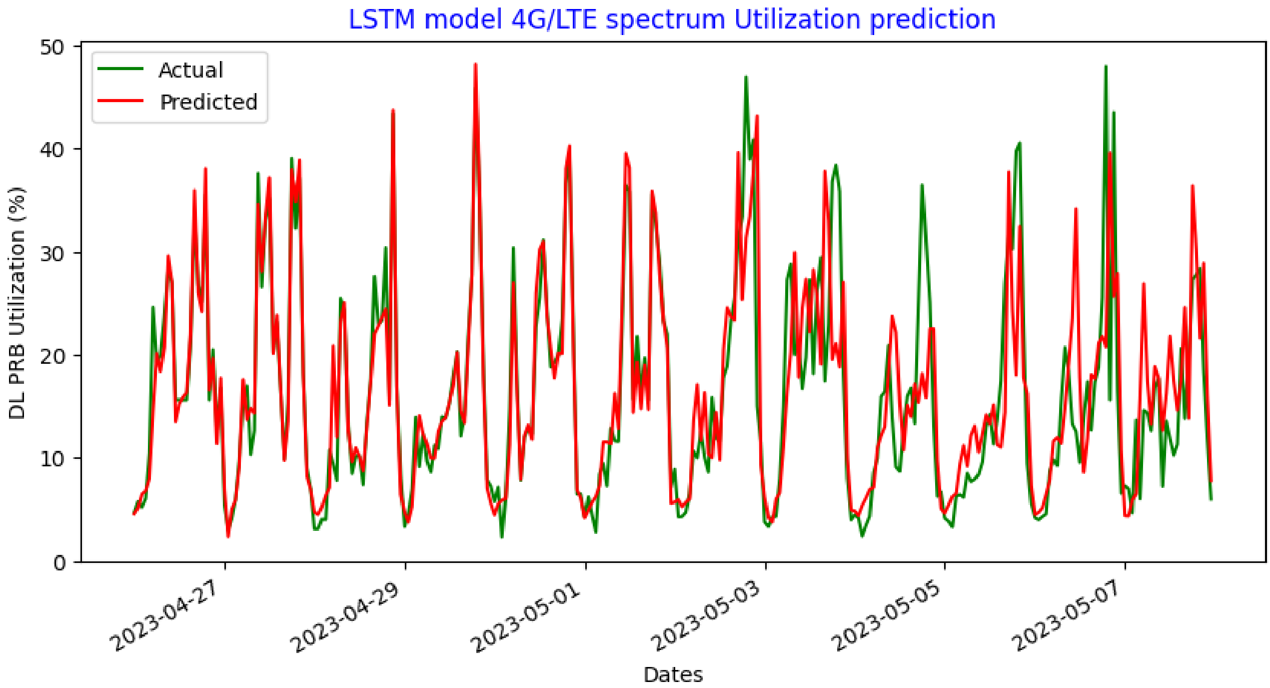


Figure 4.3.1: LSTM Model Prediction vs. Actual Value.

4.3.2 CNN Modeling for Spectrum Utilization

To improve the performance of CNN models, hyperparameters such as learning rate, batch size, number of epochs, and regularization methods can be tuned. The optimal values for these hyperparameters depend on the specific problem and dataset being used and can be determined through experimentation and validation.

In this work, the values carefully showcased in the illustrious Table 4.3.2 have been derived through an ingenious and rigorous process known as grid search. This powerful technique allows for a comprehensive exploration of all possible combinations, ensuring that no avenue is omitted in the search for the best outcomes. By employing this method, researchers [47] have been able to extract invaluable insights and unlock hidden patterns, revolutionizing the field in unimaginable ways.

These finely tuned hyperparameters ensure that our model operates at its peak performance, delivering precise and reliable predictions with the utmost accuracy. Using these fine-tuned hyperparameters shown in Table 4.3.2, the built model prediction result is depicted in Figure 4.3.2.

Hyperparameters	Values
Number of Neurons	100
Pool size	2
Number of Filters	512
Kernel Size	5
Batch Size	8
Hidden Layer	1
Dropout	0.0%
Optimizer	Adam
Activation Function	ReLU
Epoch	2000

Table 4.3.2: Simulation Parameters for the CNN Framework.

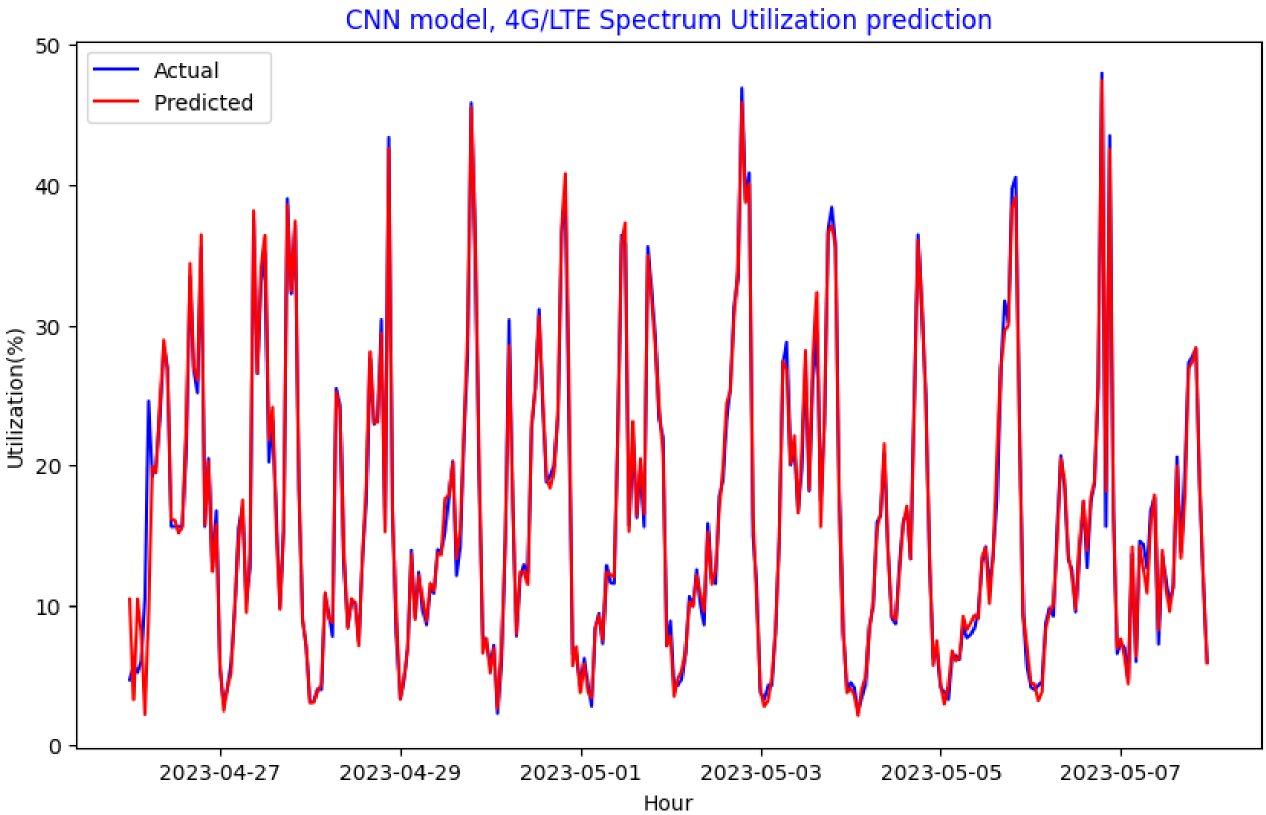


Figure 4.3.2: CNN Model Prediction.

4.3.3 Model Comparison

When evaluating the cell-level spectrum utilization prediction of the LSTM and CNN models, Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Relative Error (MRE) are taken into account. These metrics provide valuable insights into the performance and accuracy of each model. Upon analyzing the results, as clearly depicted in Table 4.3.3 and Figure 4.3.3, it becomes evident that the CNN model outperforms the LSTM model in terms of suitability for this particular task. By capturing complex patterns and dependencies within the data, the CNN model is better able to predict the future. The RMSE metric showcases that the CNN model provides a significantly lower error rate compared to LSTM. This indicates that predictions made by the CNN model are closer to the actual values, resulting in more precise spectrum utilization forecasting. Moreover, examining MAE reveals that the CNN model has a smaller average absolute deviation from ground truth values when compared to LSTM. This implies that the predictions generated by CNN are consistently closer to actual observations, exhibiting higher precision and reliability. Lastly, MRE provides an understanding of how well each model performs relative to actual data. It is evident from our analysis that the MRE for the CNN model is considerably lower than that of LSTM. This signifies that when using CNN for cell-level spectrum utilization prediction, one can expect a higher level of accuracy and fewer errors compared to utilizing LSTM. Based on these findings, it can be confidently stated that for this specific scenario involving cell-level spectrum utilization prediction, adopting a CNN-based approach is more suitable than utilizing an LSTM-based approach. The CNN model's superior performance ensures accurate and reliable predictions for sound decision-making in dynamic spectrum-sharing tasks.

	RMSE	MAE	MRE
LSTM	5.8	3.5	0.000078
CNN	1.3	0.9	0.000014

Table 4.3.3: Model Performance Evaluation.

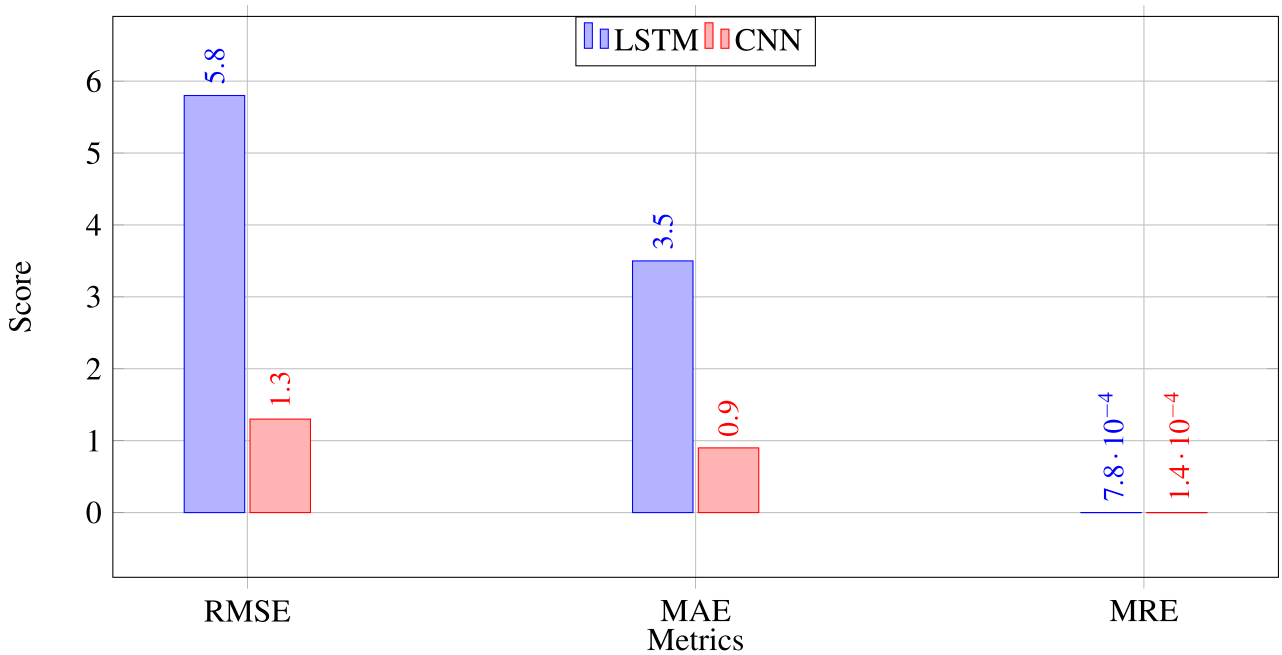


Figure 4.3.3: LSTM vs. CNN.

4.4 Traffic Modeling

This thesis assumes that each RAT has one UE scheduled to use all available resources. The DSS controller determines resource allocation by considering the final day of the best-fit machine learning prediction, which is the 24-hour utilization of LTE PRB. This enables the allocation of resources for 5G NR using only unused spectrum resources from legacy users. The in-used data is shown in Figure 4.4.1.

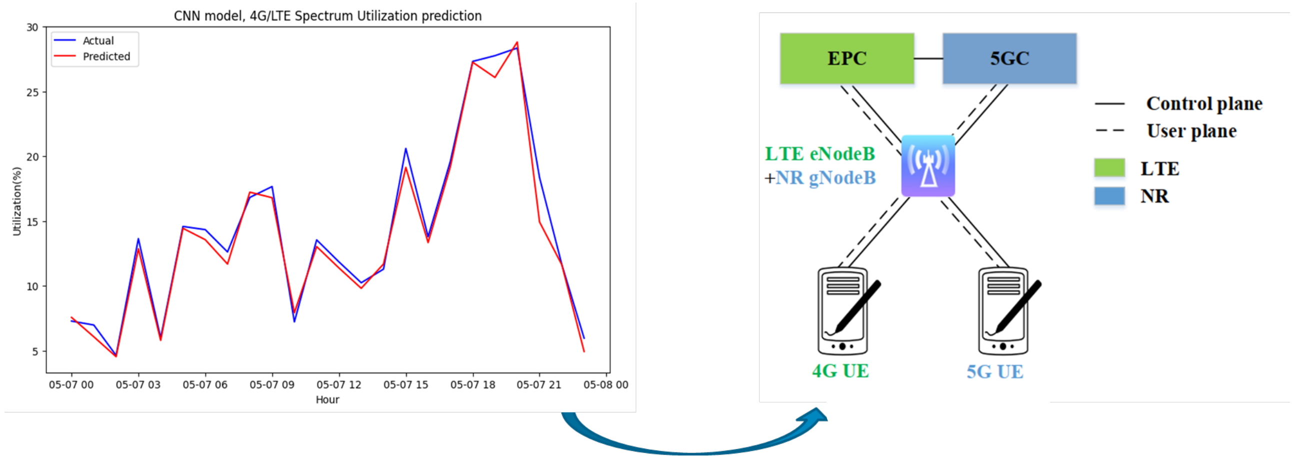


Figure 4.4.1: DL LTE PRB Utilization as Input for Real-time Bandwidth Split.

4.5 Channel Model

The simulation of the communication channel between a UE and its serving BS is achieved through several calculations. First, the 3GPP Urban Macro propagation model with clustered delayed line (CDL-C) [54] is assumed for the channel model. This model takes into account the specificities of the urban environment in which the UE and its BS operate. Then, the path loss between the UE and its serving BS is calculated using Equation 3.6. This model considers the 2.6 GHz frequency band, which is known for its high data transfer rates, and the distance between the UE and the BS in meters. The resulting path loss value is used to calculate the SNR of the UE-BS link. This SNR value is calculated using Equation 3.8, which takes into account several factors such as the transmit power of the BS or RAT to the UE over a specific RB, the noise power spectral density, and the bandwidth of the RB. The noise power spectral density can be calculated using Equation 3.9, by considering bandwidth and equivalent temperature.

4.6 RE-Level Rate Matching DSS Simulation Setup

The controller's decision to split the bandwidth is based on the best-fit machine learning model prediction result. As discussed prior, RE-level rate-matching is more efficient than other DSS techniques. SNR is our main focus to evaluate our system's performance in terms of throughput and spectral efficiency. By assuming that interference such as inter-cell and adjacent channel interference has been disregarded, we can determine whether or not the system performs adequately in a specific location.

In this study, we made use of the powerful Matlab Toolbox 2022 for our analysis and implementation of dynamic spectrum-sharing techniques. The built-in RE-level rate-matching DSS functionality of this toolbox was the primary factor in our decision to use it. By leveraging this feature, we were able to effectively control the SNR level within the system and optimize resource allocation.

4.6.1 Physical Channels and Signal Mapping to Resource Grid

This section demonstrates how to generate a waveform that includes multiple channels for use in both 5G NR and LTE networks. The channels included are absolutely crucial and cannot be overlooked. They comprise of 5G PDSCH, LTE CRS, LTE PSS, LTE SSS, LTE PBCH, LTE PDCCH , LTE PCFICH, and LTE PHICH.

The 5G PDSCH occupies all resources that are not used by the LTE waveform. This means that the 5G NR system utilizes the frequency spectrum that is not being used by the LTE system, thereby avoiding interference between the two systems.

Figures 4.6.1 and 4.6.2 show sample resource grids of LTE and 5G NR while they share 28 and 72 PRBs respectively, out of the total available 100 PRBs.

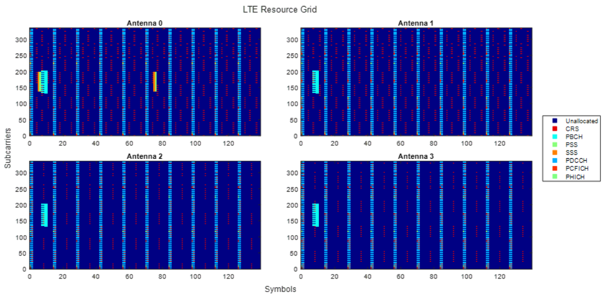


Figure 4.6.1: LTE Resource Grid.

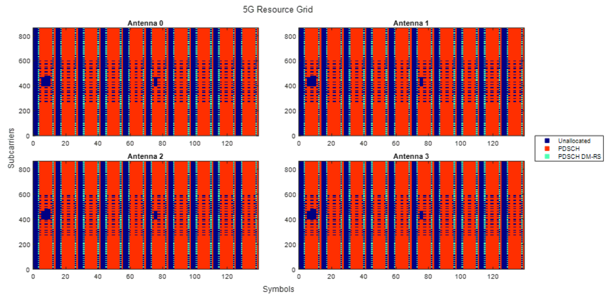


Figure 4.6.2: 5G NR Resource Grid.

4.6.2 DSS Performance Evaluation

For the LTE case, the physical layer is being configured to align with the existing configuration of Ethio telecom's site. The configuration includes setting the modulation, target code rate, number of MIMO, and bandwidth as shown in Table 4.6.1a. For the 5G NR side, we have taken the following consideration.

	LTE	5G NR
Modulation	64QAM	256QAM
MIMO	4T2R	4T2R
Code Rate	0.5	0.75
Bandwidth	20MHz	20MHz

(a) Physical Layer Configuration Parameters.

Parameter	Value
Tx Power	43.617 [dbm/0.23w/PRB]
Path Loss	111.9579 [dB]
Noise power	126.8491 [dBm/PRB]
Propagation channel Model	CDL-C model (Uma)

(b) Radio Link Parameters.

Table 4.6.1: Radio Environment Simulation Parameters.

Equations (3.6-3.7) are used to calculate the Tx power, pathloss, and noise power spectral density at the cell center, specifically at a distance of 200 meters away from the eNB. The calculated values are then presented in Table 4.6.1b, which provides a clear overview of the results. Additionally, the SNR value is also calculated and presented, which is 23dB in this case. These values are then used to

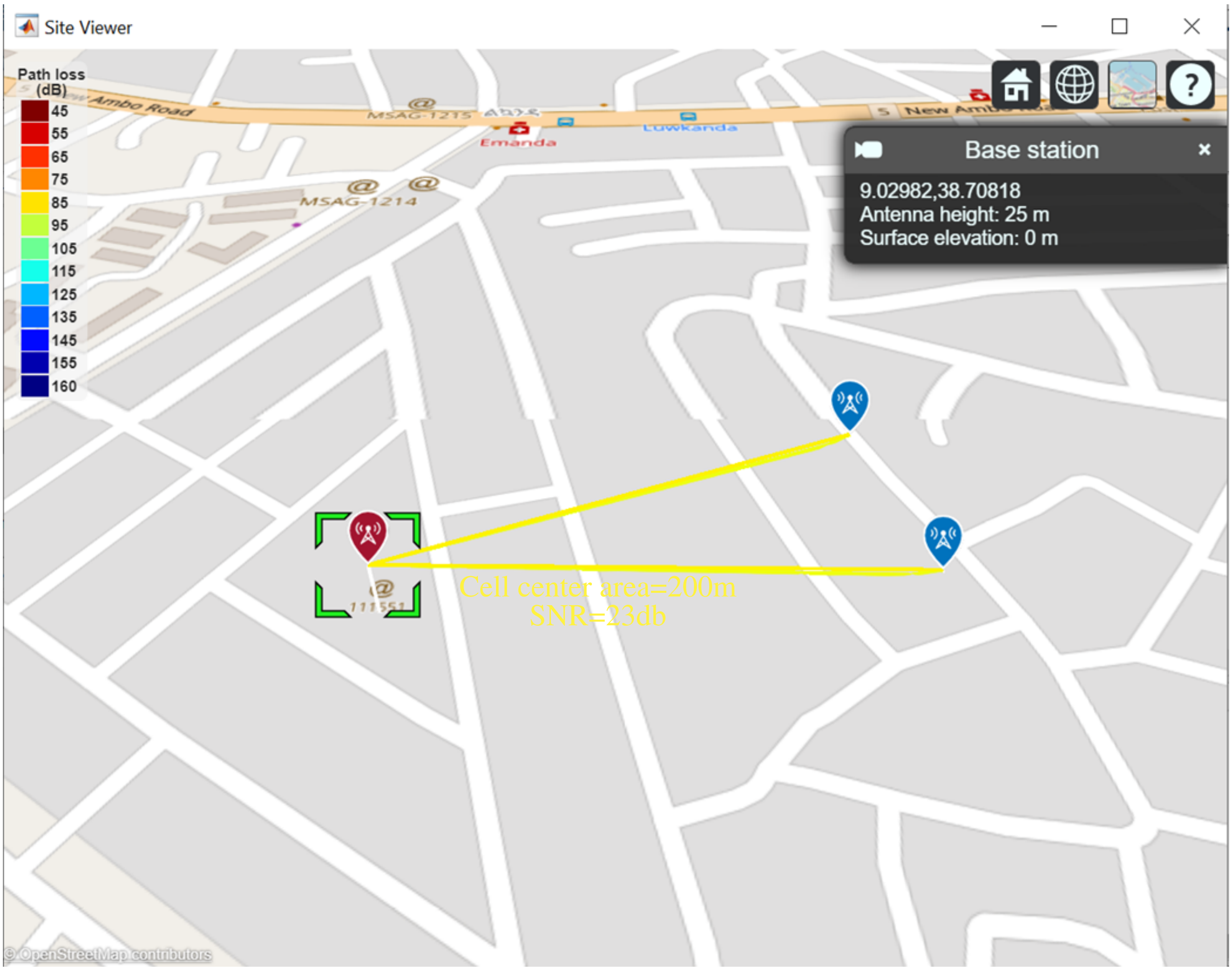


Figure 4.6.3: Site Configuration.

visualize the instantaneous LTE and 5G NR values in Figure 4.6.4 and 4.6.5. The visualization helps to provide a better understanding of the data and allows for easier interpretation of the results.

The average DSS LTE and NR throughput per day is 8.7 Mbps and 107.7216 Mbps, respectively. Consequently, Using Equation 3.11 the achieved average DSS spectral efficiency is 5.82$bit/sec/Hz$. For the same PRB demand, the existing LTE network has a daily average throughput, and spectral efficiency are 8.7892 Mbps, and 0.43 $bit/sec/Hz$, respectively.

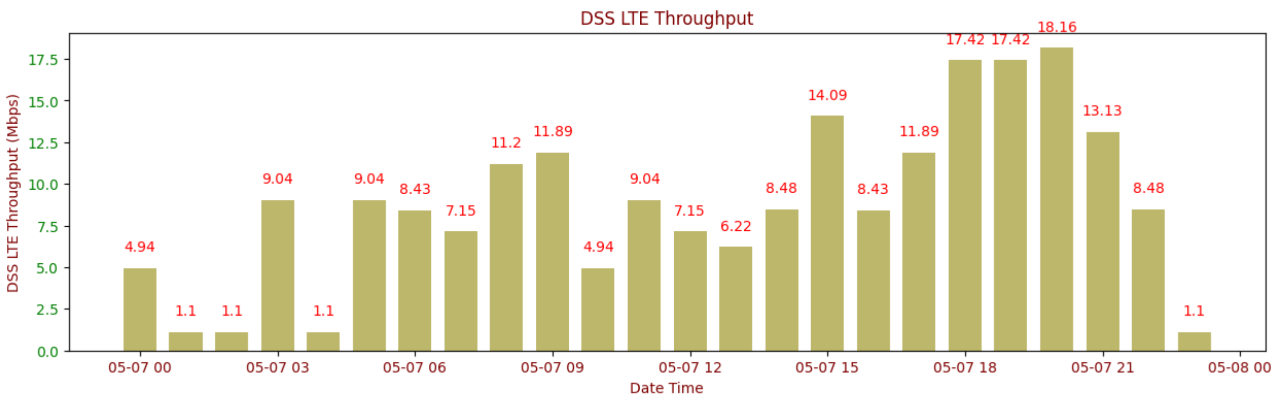


Figure 4.6.4: DSS LTE Instantaneous Throughput.

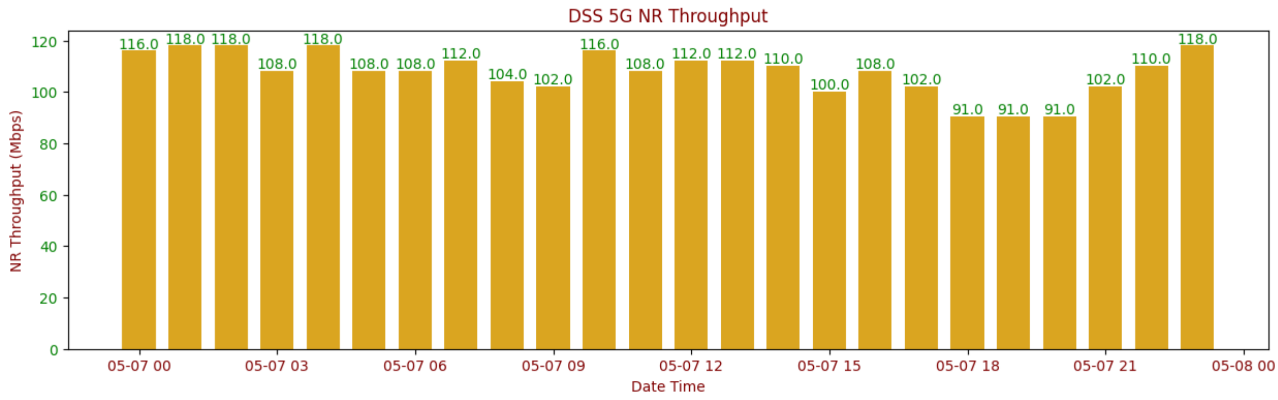


Figure 4.6.5: DSS NR Instantaneous Throughput.

In addition, we conducted throughput measurements at various locations within the coverage area of eNB to determine the performance of different RAT relative to their maximum achievable throughput. The existing site configuration has a maximum cell radius of 400 meters. Our objective is to utilize unused spectrum in this region based on the LTE network's PRB demand. During our measurements, we took into account the peak PRB demand observed in the network to accurately reflect the network's performance under high-demand conditions.

At a distance of 400m, the SNR is measured to be 13 dB. According to Table 4.6.1, when using this parameter value, LTE's performance deteriorates by only 5 percent in this scenario. However, NR experiences a significantly larger degradation of around 50 percent.

Based on our findings shown in Figure 4.6.6 and 4.6.7, it is evident that there is a noticeable difference between the impact on LTE and NR networks at this distance. While LTE exhibits relatively minor degradation in performance with a decrease of only 5 percent under these conditions, NR suffers from substantial deterioration by approximately half its original capacity. Based on these findings, it is clear that the distance-related noise will have a significant impact on the performance of 5G NR compared to LTE.

One way to improve performance is to use adaptive modulation order. Adaptive modulation order refers to the ability of the base station to adjust the modulation order based on the SNR. This means that the base station can use a higher modulation order (which provides more data per symbol) when the SNR is good, and a lower modulation order when the SNR is poor. This can help to improve the performance of 5G NR at longer distances.

Another way to improve performance is to use various TX power levels. The base station can also adjust the TX power level based on the distance to the user. This means that the base station can use a higher TX power level when the user is further away, and a lower TX power level when the user is closer.

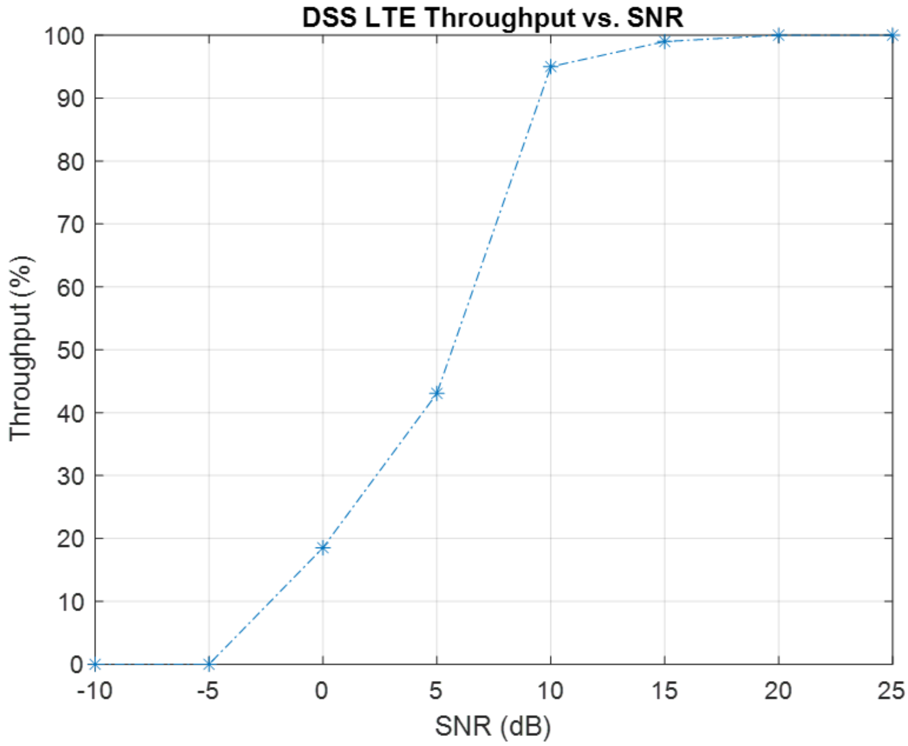


Figure 4.6.6: DSS LTE Throughput(%) vs. SNR Points.

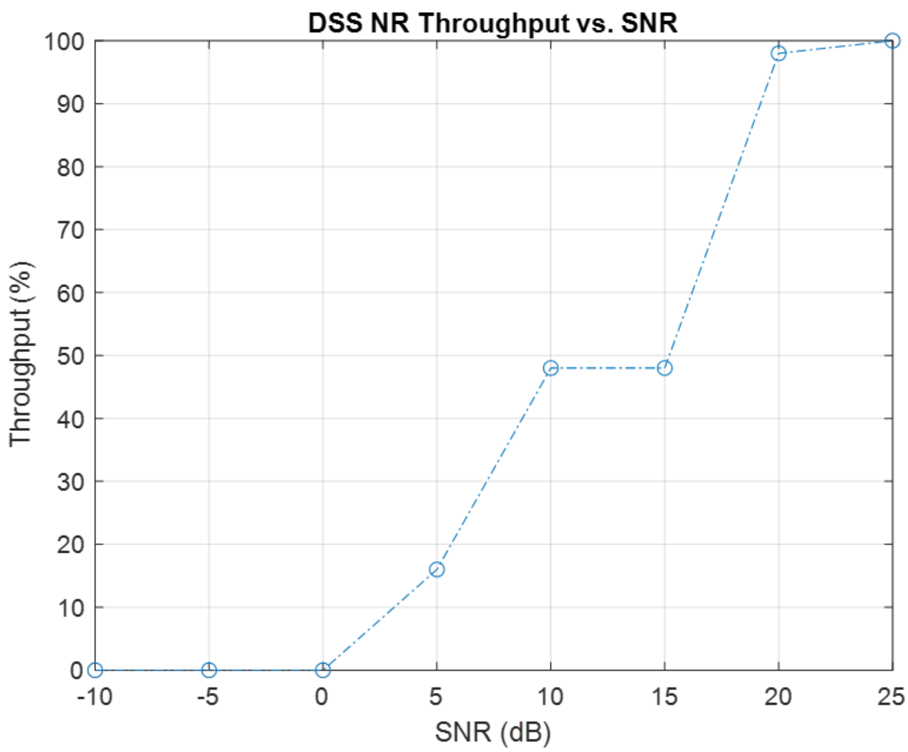


Figure 4.6.7: DSS NR Throughput(%) vs. SNR Points.

4.7 Comparison between Machine Learning-based DSS and SSS

By setting the PRB utilization at 50% and the SNR at 23 dB, we conducted a thorough comparison between DSS and SSS performance. This analysis took into account the parameter values stated in Table 4.6.1. Figure 4.7.1 clearly demonstrates that when assuming optimal resource allocation for both Radio Access Technologies and disregarding any impact of resource allocation, RE-level rate-matching DSS compromises approximately 32.54% of NR performance compared to SSS or non-DSS NR. The impact on throughput arises from the reduction in NR PDSCH symbols and the rate matching of LTE CRS when utilizing all NR channels for data, control, and reference signals. It is important to note that LTE performance remained unaffected by DSS throughout our investigation. The overall cell performance is significantly increased by implementing DSS, as it allows for the simultaneous utilization of LTE and NR resources.

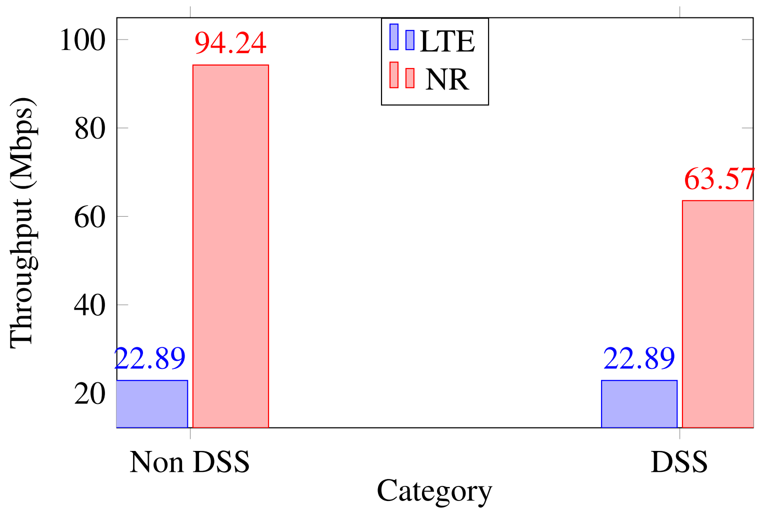


Figure 4.7.1: Capacity Comparison between DSS and SSS.

Chapter 5

Conclusion and Recommendation

5.1 Conclusion

This study evaluated the performance of a DSS at the link level using ML-based spectrum utilization modeling and RE-level rate-matching. The data was obtained from Ethio telecom's PRS of an eNB operating at 2600 MHz in Addis Ababa.

The findings offer valuable insights to operators regarding the choice of robust spectrum sharing between LTE and 5G NR. The analysis clearly demonstrates that the utilization of machine learning models plays a crucial role in effectively allocating spectrum resources, thereby preventing QoS degradation caused by reactive allocation methods and RATs' greedy behavior. By leveraging advanced ML algorithms, operators can optimize spectrum resource distribution for both LTE and 5G NR networks, ensuring improved QoS performance while minimizing interference issues.

In addition to prioritizing the QoS assurance for LTE services, efforts have been made due to its wide deployment and well-established utilization pattern. However, the early-stage deployment of 5G poses challenges in understanding its utilization pattern. To achieve significant improvements, the use of LSTM and CNN models have been compared. Among these two models, it was observed that the CNN model outperformed in solving complex problems for the given task. CNN's ability to handle intricate problem domains allowed it to excel and deliver superior performance compared to LSTM. Therefore, based on our evaluation results, we recommend using the CNN model as it has demonstrated a higher level of effectiveness in addressing complex tasks.

The proposed model for RE-level rate matching dynamic spectrum sharing involves the use of 24-hour prediction data. This is done in order to mitigate the impact of RE-level rate-matching DSS channel collisions on the performance of the existing LTE network. In order to further improve the performance of the proposed model, NR side puncturing has been implemented.

To evaluate the performance of the proposed model, tests were conducted at different SNR points in terms of throughput and spectral efficiency. The results showed that the performance of 5G NR degrades rapidly at the cell edge, dropping to 50%. However, the overall performance of the proposed model is significantly better than that of static spectrum sharing.

To confirm that the proposed model has no adverse impact on the existing LTE network, a comparison with static spectrum sharing was conducted. The results showed that while the DSS 5G NR experienced around 32.54% degradation, LTE remained unaffected. This indicates that the proposed model is a viable solution for improving the performance of dynamic spectrum sharing while minimizing the impact on the existing LTE network.

5.2 Recommendation

The methodology and analysis provided are excellent solutions for efficiently utilizing spectrum, boosting cell capacity, and rolling out 5G NR in lower-frequency bands. The study's findings can be used to inform the following recommendations.

- Ethio telecom is presently implementing 5G on a new mid-band frequency of 3500 MHz. However, this may result in additional expenses for the deployment of new sites. It is possible to implement 5G NR on current infrastructure with the help of DSS, which is an effective way to reduce costs.
- The result can be a viable solution for enhancing spectrum efficiency and cell capacity.
- In the future, once 5G technology becomes widely adopted, the aim is for all frequency bands to support 5G connectivity. This will allow us to aggregate them together in order to achieve the highest levels of performance and efficiency.

Looking ahead, it would be beneficial to explore the effects of interference on the DSS network, including both co-channel interference and adjacent channel interference. Furthermore, its enhancement of techno-economic effects is another valuable aspect.

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Appendix

Machine Learning-Based Spectrum Utilization Prediction for Dynamic Spectrum Sharing between 4G LTE a 5G NR

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***Abstract*—Dynamic spectrum sharing (DSS) enables the coexistence of 4G LTE and 5G NR networks in the same frequency band, allowing for more efficient utilization of scarce spectrum resources. This paper proposes a machine learning (ML) based approach to predict LTE spectrum utilization and enable intelligent DSS between LTE and NR. A comprehensive data set collected over 124 days from an LTE base station in Addis Ababa forms the foundation. Long Short-Term Memory (LSTM) and Convolutional Neural Network (CNN) models are developed and evaluated using standard metrics. The CNN model demonstrates superior performance in predicting future spectrum utilization patterns. Using the CNN prediction, a RE-level rate-matching DSS technique is implemented and assessed through simulations. Results showcase that the proposed strategy significantly enhances bandwidth utilization while ensuring minimal degradation of LTE performance. Comparisons with static spectrum sharing strategies prove the efficacy of the proposed approach. This novel methodology enables intelligent DSS by leveraging ML for prediction and proactive resource allocation.**

***Index Terms*—Dynamic spectrum sharing, machine learning, deep learning, LSTM, CNN, LTE, 5G NR.**

I. Introduction

With the emergence of 5G NR networks, dynamic spectrum sharing (DSS) has gained traction as an efficient technique to share spectrum between 4G LTE and 5G NR technologies [1]. By enabling the flexible allocation of bandwidth between LTE and NR users based on traffic demands, DSS allows for better utilization of scarce spectrum resources.

However, optimally implementing DSS requires accurately predicting future spectrum utilization patterns [2]. This paper proposes a novel machine learning-based approach for LTE spectrum utilization forecasting to enable intelligent DSS decisions.

The key contributions are:

- Development and comparison of LSTM and CNN models for predictive modeling of LTE spectrum utilization using real network data.
- Implementation of an RE-level rate matching DSS technique driven by the ML forecast.
- Extensive evaluation of the proposed model's performance impact and comparisons with static sharing strategies.

The main objective is to develop an efficient and robust DSS strategy between 4G LTE and 5G NR networks by leveraging machine learning-based spectrum utilization prediction. Accurately forecasting the spectrum utilization patterns is crucial for optimally implementing DSS and dynamically allocating bandwidth between LTE and 5G NR users based on traffic demands. The proposed machine learning-based prediction approach enables intelligent and proactive decision-making by the DSS controller regarding resource allocation between the two networks. Leveraging advanced deep learning algorithms like LSTM and CNN allows for capturing complex temporal relationships in cellular traffic usage from real network data. The subsequent integration of the forecast into an RE-level rate-matching DSS technique powered by simulations facilitates thorough performance assessment across various operating conditions. Comparisons to static spectrum sharing approaches provide useful insights into the efficacy of the proposed data-driven methodology for enhancing bandwidth utilization, spectral efficiency, and overall network capacity while ensuring minimal impact on legacy LTE networks. The development of an efficient spectrum-sharing strategy is key to addressing the increasing spectrum crunch faced by cellular operators and paving the way for accelerated 5G rollout.

The remainder of the paper is organized as follows. Section II presents related works. Section III describes the system model and proposed approach. Section IV analyzes the results obtained from simulations. Finally, Section V gives the conclusion.

II. Related Works

Prior works have explored various techniques for spectrum utilization modeling and DSS. Authors in [3] employed machine learning in the space, time, and frequency domains to improve 4G signal detection for Dynamic Spectrum Access (DSA). k-Nearest Neighbors and Random Forest algorithms-based models for detection to enable DSA and simulation results show significant improvement in detection probability. The work [6] analyzed efficient DSS methods between LTE and NR. Challita and Wu [4] proposed a deep reinforcement learning-based model for dynamic spectrum sharing between LTE and 5G NR. The proposed approach outperforms baseline algorithms and achieves optimal bandwidth splits in various scenarios, including Multimedia Broadcast multicast service Single Frequency Network (MBSFN) subframes, periodic high interference, mixed services, and time multiplexing.

Study [6] investigates the implementation and benefits of DSS in LTE-NR networks to improve spectrum efficiency with interference mitigation and enhanced scheduling. It introduces R16/R17 DSS enhancement schemes and highlights the impact of co-frequency interference on DSS performance, underscoring the importance of efficient interference avoidance.

A key research gap identified from the literature is the lack of sufficient investigation into data-driven deep learning strategies for forecasting spectrum utilization and enabling intelligent DSS decisions in real networks. This paper addresses this gap by leveraging LSTM and CNN for prediction.

III. Proposed Model and Methodology

This section describes the overall system model, data preprocessing, ML modeling, DSS technique, and simulation parameters.

A. System Model

The ML model operates on top of the DSS controller, as depicted in Fig. 1. The controller determines resource allocation based on the ML prediction. RE-level rate matching DSS is implemented using the forecast.

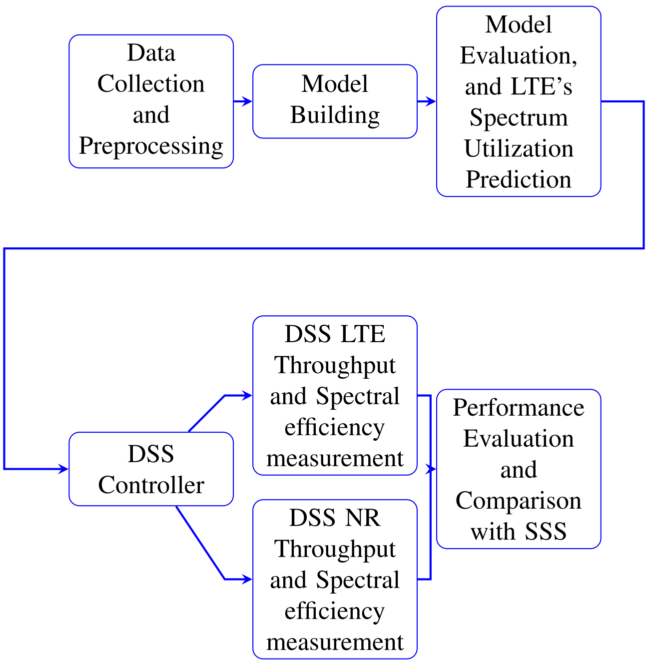

Fig. 1. System Model.

B. Dataset and Preprocessing

A dataset collected over 124 days from an LTE base station in Addis Ababa was used. It contained hourly aggregate PRB utilization for the 2600 MHz band. Outliers and missing values were handled via interquartile range and median substitution respectively.

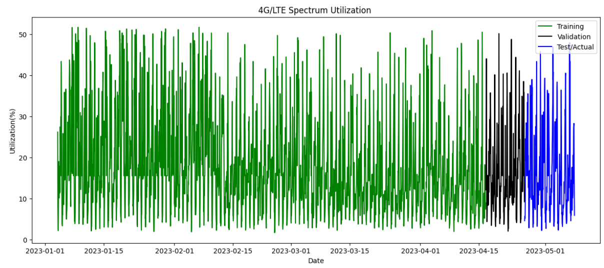

Fig. 2. Preprocessed Dataset.

C. ML Modeling

LSTM and CNN models were developed using Keras with Tensorflow backend.

1) LSTM Modeling for Spectrum Utilization: LSTM is a powerful RNN cell with three gates that allow it to learn long-term dependencies in sequences. The input gate determines how much new information to add to the cell state, the forget gate determines how much old information to remove, and the output gate determines how much of the cell state to output. This makes LSTM well-suited for tasks such as dynamic spectrum sharing, where it can be used to predict future usage patterns and efficiently manage the limited radio spectrum.

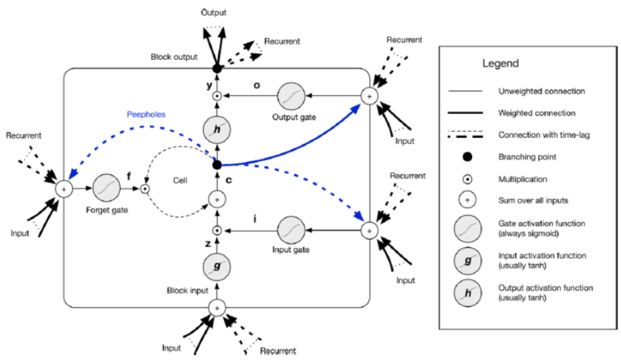

Fig. 3. LSTM Block Diagram [10].

2) CNN Modeling for Spectrum Utilization: Convolutional neural networks (CNNs) are powerful machine learning tools that can be used to solve a wide range of problems, including image classification, face recognition, time series forecasting, and text recognition. CNNs are inspired by the structure of the visual cortex in the human brain and are designed to automatically learn and extract features from data. In time series forecasting, CNNs can be used to represent a sequence of observations as a 1D image and extract the most salient features from it. This can be used to improve the accuracy of forecasts by identifying patterns and trends in the data that would be difficult to detect using traditional methods.

CNNs consist of convolutional, pooling, and fully connected layers. The convolutional layers extract features from the input data, the pooling layers reduce the size of the output, and the fully connected layers classify the data. In the case of time series forecasting, a 1D convolution is used to extract temporal information. This is done by applying a filter to the time series and sliding it over the data. The filter has one dimension, which is the time dimension, as opposed to two dimensions (width and height) in the case of images.

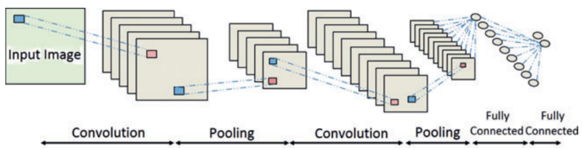

Fig. 4. Architecture of CNN Algorithm [42].

IV. Dynamic Spectrum Sharing Technical Framework

5G NR networks are promising solutions to address spectrum constraints and enhance wireless communication capability. 3GPP proposed NR to support flexible resource allocation between 5G NR and LTE in the same band of spectrum. DSS is a concept that allows LTE and 5G NR to share the same frequency bands, improving spectrum utilization efficiency. NR provides a scalable and flexible physical layer design with multiple numerologies and SubCarrier Spacings (SCS).

A. Options for Dynamic Spectrum Sharing Deployment

DSS allows NR users to be scheduled in LTE subframes while avoiding collisions with LTE CRS. There are two primary deployment options: MBSFN subframe and non-MBSFN or rate matching [7].

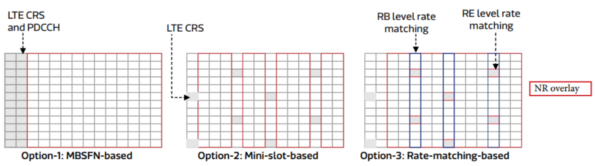

Fig. 5. DSS Deployment Options [7].

1) MBSFN Subframe Based Dynamic Spectrum Sharing: MBSFN stands for Multimedia Broadcast Multicast Service Single Frequency Network. It is a broadcast/multicast transmission technique used in LTE networks to efficiently deliver multimedia content to multiple users simultaneously. In the context of [7], MBSFN subframes are discussed as a possible option for implementing DSS to enable the coexistence of 5G NR and 4G LTE. Despite its effectiveness, there are a few potential limitations such as fixed structure, limited availability, limitations on scheduling, and interference avoidance. The LTE standard stipulates that not all subframes can be used for MBSFN; it cannot be used in certain subframes, for instance, subframe 0/4/5/9 as it contains synchronous signal and paging channel [8].

2) Non-MBSFN Subframe based Dynamic Spectrum Sharing: Non-MBSFN Subframe-based DSS is another DSS technique for enabling the coexistence of 5G NR and 4G LTE. It uses non-MBSFN subframes in LTE networks to send 5G NR signals, which is more complicated than MBSFN-based DSS in terms of allocating resources and managing interference [7].

Two options for dealing with non-MBSFN subframes containing LTE reference signals are minislot scheduling and CRS rate matching. Mini-slot scheduling is not suitable for eMBB applications but can be used for special cases like 30 kHz Synchronization Signal Block (SSB) insertion. CRS rate matching is expected to be the most commonly used option for NR data channels and can be implemented at RB or RE level as depicted in Figures 5 and 6.

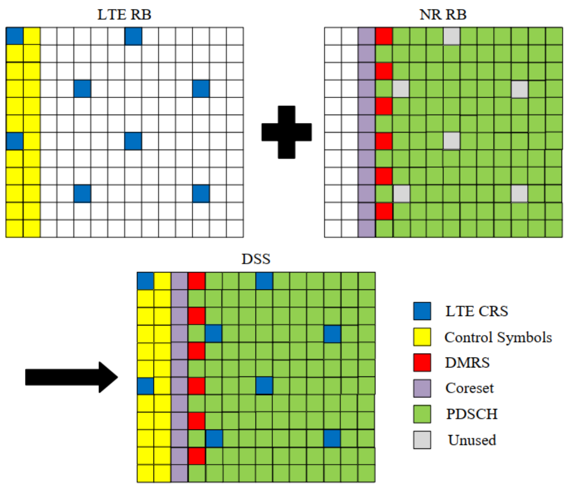

Fig. 6. Rate Matching Schematic Diagram [9].

B. Simulation Parameters

1) Machine Learning-Based Spectrum Utilization Modeling: Hyperparameter optimization and regularization are essential for developing high-performing LSTM and CNN models. Hyperparameters, such as the number of layers, hidden units, learning rate, batch size, epochs, number of filters, kernel size, pooling layer type, and activation functions, can be tuned to optimize the model's performance on the training data. Regularization techniques, such as dropout, can be applied to prevent overfitting and improve generalization.

In this work, we used the grid search algorithm to find the best combination of hyperparameters for our LSTM and CNN models. The results of the hyperparameter tuning and the models' predictive capabilities are shown in Table 4.3.1 and Figure 4.3.1, respectively.

Hyperparameters	LSTM Values	CNN Value
Number of Filters	-	128
Kernel Size	-	5
Pooling Layer	-	2
Hidden Layer	5	1
Number of Neurons	500	
Bach Size	32	32
Dropout	0.20%	0
Optimizer	Adam	Adam
Activation	ReLU	ReLu
Epoch	1000	200

TABLE I
SIMULATION PARAMETERS FOR THE LSTM AND CNN FRAMEWORK.

2) DSS Performance Evaluation: The simulation of the communication channel between a UE and its serving BS is achieved through several calculations. First, the 3GPP Urban Macro propagation model with clustered delayed line (CDL-C) [54] is assumed for the channel model. This model takes into account the specificities of the urban environment in which the UE and its BS operate. Then, the path loss between the UE and its serving BS is calculated using Equation 3.6. This model considers the 2.6 GHz frequency band, which is known for its high data transfer rates, and the distance between the UE and the BS in meters. The resulting path loss value is used to calculate the SNR of the UE-BS link. This SNR value is calculated using Equation 3.8, which takes into account several factors such as the transmit power of the BS or RAT to the UE over a specific RB, the noise power spectral density, and the bandwidth of the RB. The noise power spectral density can be calculated using Equation 3.9, by considering bandwidth and equivalent temperature.

$$Thr_{n,m} = B.log_2(1 + SNR_{n,m}) \tag{1}$$

$$SNR_{n,m} = \frac{P_t G_t G_r}{P_l N_0 B} \tag{2}$$

$$N_0 = \sqrt{\frac{1}{2} KBT_e} \tag{3}$$

$$T_e = T_{Ant} + 290 * (NF - 1) \tag{4}$$

Table II summarizes the key simulation parameters including channel models, transmission configurations, and propagation parameters.

TABLE II
SIMULATION PARAMETERS

Parameter	Value
LTE Modulation	64QAM
LTE Bandwidth	20MHz
NR Modulation	256QAM
Channel model	CDL-C
Carrier frequency	2.6 GHz

V. RESULTS AND ANALYSIS

The predictive performance of LSTM and CNN models was evaluated on a held-out test set of 10% of the total dataset. This means that the models were evaluated on a set of data that they had not seen before during training. This is important to ensure that the models are able to generalize to new data and are not simply overfitting to the training data.

These finely tuned hyperparameters ensure that our models operate at their peak performance, delivering precise and reliable predictions with the utmost accuracy. Using these fine-tuned hyperparameters shown in Table I, the built model prediction results are depicted in Figures 7 and 8.

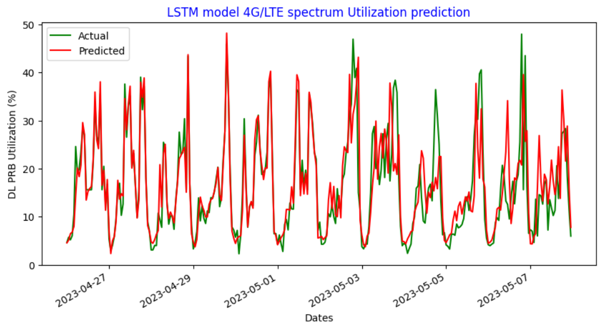

Fig. 7. LSTM Model Prediction vs. Actual Value.

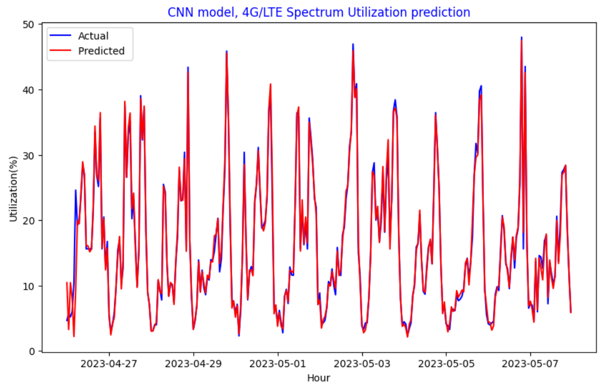

Fig. 8. CNN Model Prediction.

The CNN model outperforms the LSTM model for cell-level spectrum utilization prediction because it can better capture complex patterns and dependencies in the data. This results in more precise predictions, as evidenced by lower RMSE, MAE, and MRE metrics.

For example, a CNN model with an RMSE of 1.3 indicates that its predictions are, on average, 1.3 units away from the actual values. An LSTM model with an RMSE of 5.8, on the other hand, indicates that its predictions are, on average, 5.8 units away from the actual values. This means that the CNN model's predictions are closer to the actual values, on average.

Similarly, lower MAE and MRE values indicate that the CNN model's predictions are more accurate relative to actual data.

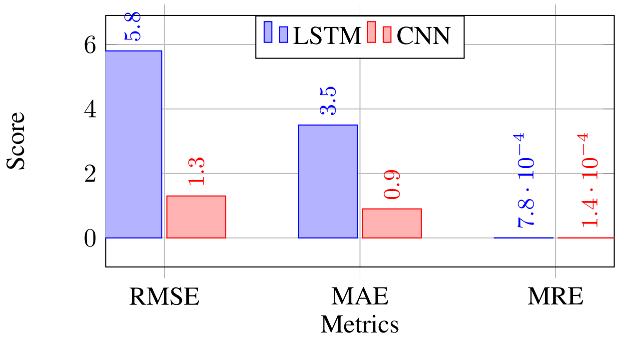

Fig. 9. LSTM vs. CNN.

The average LTE and NR throughput achieved using the proposed model was 8.7Mbps and 107.7216Mbps respectively. The spectral efficiency was 5.82bits/sec/Hz, showcasing significant gains.

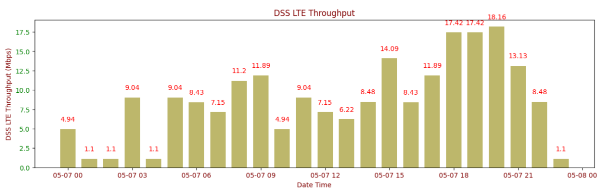

Fig. 10. DSS LTE Instantaneous Throughput.

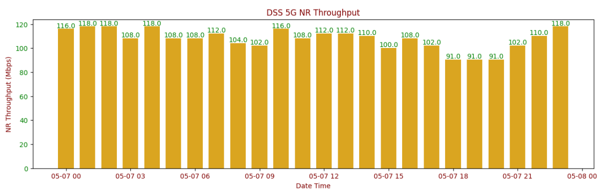

Fig. 11. DSS NR Instantaneous Throughput.

Throughput measurements at various locations within the coverage area of eNB showed that LTE's performance deteriorates by only 5% at 400m, while NR's performance degrades by 50%. This is due to the distance-related noise, which has a significant impact on the performance of 5G NR compared to LTE.

In order to improve the efficiency of 5G NR, it is possible to incorporate adaptive modulation order and employ a range of TX power levels. This enhancement is made possible by allowing the base station to automatically adjust the modulation order and TX power level according to the user's distance and signal-to-noise ratio (SNR), respectively. This way, the system can ensure optimal performance while delivering reliable connectivity to all users.

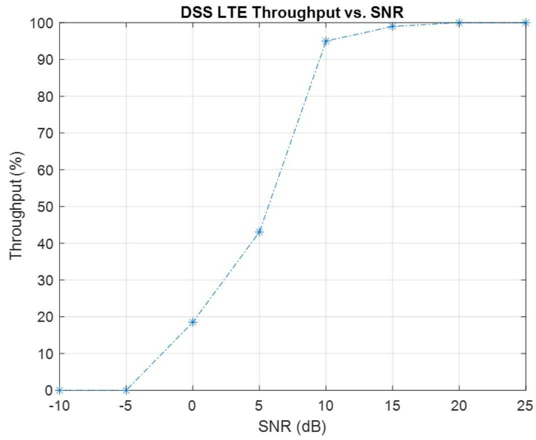

Fig. 12. DSS LTE Throughput(%) vs. SNR Points.

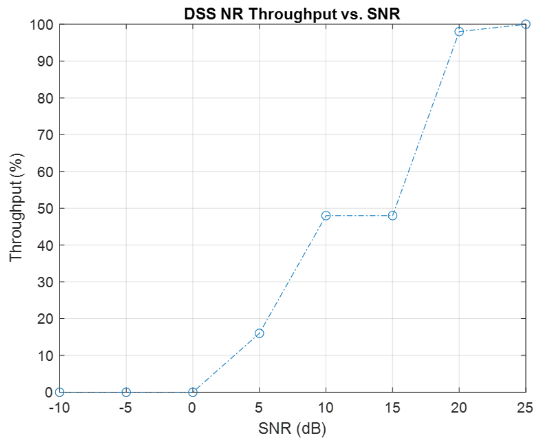

Fig. 13. DSS NR Throughput(%) vs. SNR Points.

As highlighted in Fig. 14, LTE performance remained unaffected even at low SNR levels. However, NR throughput was reduced by 50% at low SNR. Still, overall cell capacity improved substantially compared to static sharing.

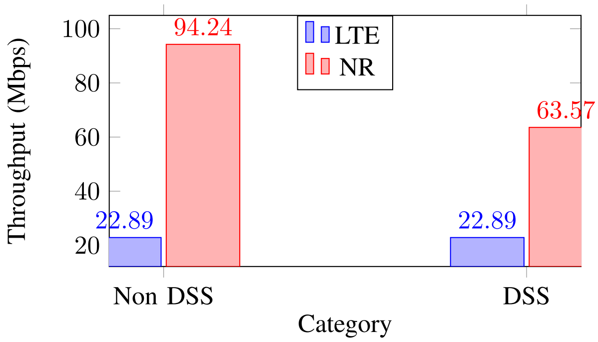

Fig. 14. Capacity Comparison between DSS and SSS.

These results validate the efficacy of the proposed approach in optimizing DSS using ML prediction while ensuring minimal LTE performance degradation.

VI. Conclusion

This paper demonstrates a novel ML-based technique to forecast LTE spectrum utilization and implement predictive DSS between LTE and 5G NR. Comparisons with static sharing strategies prove the proposed methodology's effectiveness in optimizing spectrum efficiency. The data-driven deep learning approach provides a robust, proactive solution for intelligent DSS in real networks. As future work, analyzing the impact of interference and further tuning the model using additional data would be beneficial.

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