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

LTE PRB utilization prediction for load balancing between frequency layers

by:

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Declaration

I declare that this thesis is entirely my own work and does not include any content from other educational institutions without proper acknowledgement. To the best of my knowledge, it does not contain previously published material by another person without recognition.

Fetihya Mohammed	Signature	Date
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ABSTRACT

The ever-increasing number of smart devices and services strains Long-Term Evolution(LTE) network capacity, impacting Key Performance Indicators(KPIs) like user experience. Accurate prediction of LTE resource utilization is crucial for network optimization and improving user experience. Physical Resource Block (PRB) utilization prediction plays a vital role in analyzing resource allocation within the network. This thesis investigates the application of machine learning models for predicting LTE PRB utilization to facilitate load balancing between frequency layers. Three prominent models – Prophet, long short term memory (LSTM), and eXtreme Gradient Boosting(XGBoost) were evaluated and compared. The results demonstrate that Prophet significantly outperforms LSTM and XGBoost in terms of prediction accuracy. Prophet achieved an R-squared value of 0.95 and a Mean Absolute Error(MAE) of 4.98, indicating a highly accurate fit. Conversely, LSTM and XGBoost obtained R-squared values of approximately 0.63 with respective MAE values of around 17. These findings suggest Prophet's superior accuracy makes it a promising choice for predicting PRB utilization and enabling effective load balancing in LTE networks. This thesis contributes to the field of LTE network optimization by demonstrating the effectiveness of machine learning, particularly Prophet, for PRB utilization prediction. This capability can be leveraged to develop efficient load balancing algorithms that improve network performance and user experience.

Key Words: Prophet, LSTM, XGBoost, Physical resource block, MAE, R-squared.

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In conclusion, I recognize that this research would not have been possible without the support of those mentioned above. I am deeply indebted to them for their contribution and I am confident that the knowledge and skills I have gained from this experience will be invaluable in my future endeavors.

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List of Abbreviations

AMC	Adaptive Modulation and Coding
ARIMA	Autogressive Integrated Moving Average
CA	Carrier Aggregation
CDMA	Code Division Multiple Access
CIO	Cell Individual Offset
DL PRB	Down Link Physical Resource Block
EHF	Extremely High Frequencies
ELF	Extremely Low Frequencies
ETSI	European Telecommunications Standards Institute
FCC	Federal Communications Commission
FDMA	Frequency Division Multiple Access
GAM	Generalized Additive Model
GPU	Graphics Proccessing Unit
GSM	Global System for Mobile Communications
IOT	Internet of Things
IR	Infrared
KPI	Key Performance Indicator
LSA	Licensed Shared Access
LSTM	Long Short Term Memory
LTE	Long-Term Evolution
MAE	Mean Absolute Error
MCMC	Markov Chain Monte Carlo
MSE	Mean squared error
NFV	Network Function Virtualization
OFDMA	Orthogonal Frequency Division Multiplex Access
PRB	Physical Resource Block

QAM	Quadrature Amplitude Modulation
QoS	Quality of Service
RNN	Recurrent Neural Network
SARIMAX	Seasonal Auto Regressive Moving Average with eXogenous factors
SDN	Software-Defined Networking
TDMA	Time Division Multiple Access
UE	User equipment
UL PRB	Up Link Physical Resource Block
UMTS	Universal Mobile Telecommunications Service
UV	Ultraviolet
WCDMA	Wideband Code Division Multiple Access
XAI	Explainable Artificial Intelligence
XGBoost	eXtreme Gradient Boosting

Chapter 1: **Introduction**

The rapid development of wireless communication technologies like 4G LTE has revolutionized the way we access and consume information. From the proliferation of internet-connected devices or internet of things(IoT) to the widespread adoption of streaming services and video/audio platforms, mobile data usage has skyrocketed in recent years. LTE with its significantly faster speeds, has become the preferred technology for supporting these bandwidth-intensive activities[1].

This surge in mobile data demand has placed immense pressure on the available radio spectrum, a finite resource essential for wireless communication. While the scarcity of spectrum is often cited as the primary challenge, inefficient utilization further exacerbates the problem. Certain frequency bands experience heavy congestion at specific times and locations, while others remain underutilized or even unused. This uneven distribution of network traffic underscores the critical need for innovative solutions to optimize spectrum usage and ensure smooth network operation.

Predicting future resource utilization is a crucial step towards achieving efficient spectrum management in LTE networks. By analyzing historical data on resource utilization rates, we can anticipate potential congestion and proactively allocate resources across different frequency bands. This approach, known as resource utilization prediction.

Load balancing aims to distribute network traffic evenly across available resources, mitigating congestion and ensuring optimal network performance. In the context of LTE networks, load balancing involves dynamically adjusting the allocation of PRBs among different frequency bands by predicting future PRB utilization and strategically distributing traffic, load balancing algorithms can Reduce network congestion by preventing specific frequency bands from becoming overloaded. Efficient utilization of available resources allows LTE networks to accommodate a growing number of users and data traffic demands.

The traditional methods for resource allocation in LTE networks often rely on static models that may not adequately capture the dynamic nature of mobile data traffic. This is where machine learning offers a promising solution. Machine learning algorithms have the ability to learn from historical data and identify complex patterns. This capability can be leveraged to develop accurate resource utilization prediction models.

By training machine learning models on historical data collected from base stations, we can forecast future PRB utilization across different frequency bands. This predictive capability forms the foundation for developing intelligent load balancing algorithms. These algorithms can dynamically adjust resource allocation based on predicted PRB utilization rate, proactively addressing potential congestion and optimizing the overall network performance.

This thesis investigates the application of machine learning techniques for predicting future PRB utilization in LTE networks. We explore the effectiveness of various machine learning models that can contribute to the development of efficient load balancing algorithms. By leveraging the power of machine learning, we aim to optimize resource allocation and enhance network performance in the face of ever-increasing data demands.

1.1 Statement of the Problem

The issue of load imbalance, where some cells experience significantly higher traffic compared to others. This uneven distribution of loads leads to congestion in heavily loaded cells, causing PRB utilization rates to surge. As mobile users move around the network, the load within a cell is constantly changing, further complicating resource allocation. Traditional mobility load balancing techniques distribute traffic across different frequency layers, but this requires efficient management and knowledge of neighboring cell loads. To optimize network performance and user experience, it's crucial to accurately predict future resource utilization. This allows for proactive load balancing and resource allocation strategies. Additionally, spectrum efficiency, a measure of how effectively radio resources are being utilized, is a key factor in optimizing network performance. Data from Ethio Telecom dataset shows that diffrent PRB utilization rate between frequency layers as shown in the graph below, indicating inefficient resource utilization.

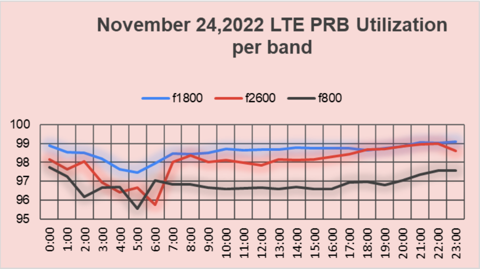


Figure 1.1: LTE PRB utilization per band

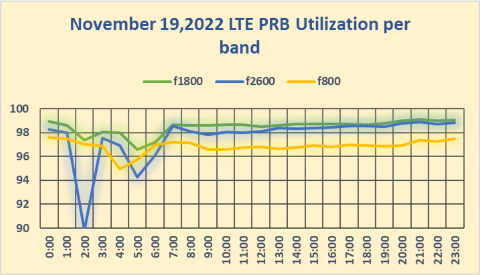


Figure 1.2: LTE PRB utilization per band

Furthermore, the dataset reveals a clear correlation between holidays and special events with increased traffic, leading to higher PRB utilization rates. Addressing these challenges through accurate PRB utilization prediction and improved spectrum efficiency strategies is essential for ensuring efficient resource allocation, mitigating congestion, and ultimately enhancing user experience in LTE networks.

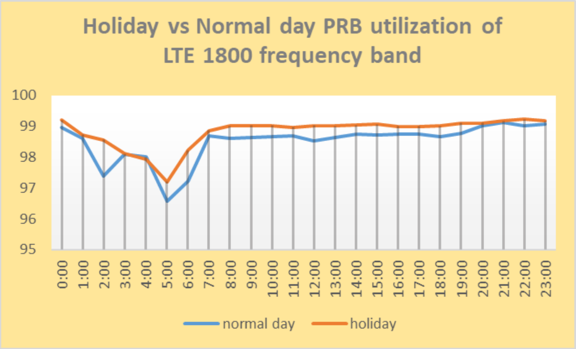


Figure 1.3: LTE PRB holiday vs normal day.

Challenges of Load Imbalance:

- Degraded Quality of Service (QoS): Congestion in overloaded cells translates into a poorer user experience. This manifests as slower data speeds, increased latency (delays in data transfer),and dropped calls. These issues can significantly frustrate users and potentially deter them from using mobile data services altogether.

- Inefficient Resource Utilization: Load imbalance can lead to underutilized resources in lightly loaded cells while heavily loaded cells struggle to meet demand. This inefficient allocation hinders the overall network capacity and spectrum efficiency.

- Limited Scalability: Traditional static load balancing methods may struggle to adapt to rapidly changing traffic patterns. This can lead to network congestion during peak hours or special events, impacting a large number of users simultaneously.

- Limited Knowledge of Neighboring Cells: Existing load balancing techniques often rely on limited information about the traffic load in neighboring cells. This hinders the ability to make informed decisions about resource allocation and can lead to suboptimal load distribution.

- Limited Prediction Capabilities: Current methods for resource allocation may not adequately capture the dynamic nature of mobile data traffic.Inability to accurately predict future traffic patterns makes it difficult to proactively address potential congestion and optimize resource allocation.
- Limited Flexibility in Resource Allocation: Traditional approaches may struggle to dynamically adjust resource allocation across different frequency layers. This limits the ability to fully utilize the available spectrum and optimize network performance. By addressing these challenges, we can move towards more efficient and user-centric LTE networks.

This thesis explores the application of machine learning techniques for predicting future PRB utilization. This capability can form the foundation for developing intelligent load balancing algorithms that dynamically adjust resource allocation based on predicted resource utilization. By optimizing resource utilization and mitigating congestion, we aim to significantly improve network performance and user experience in LTE networks.

1.2 Objective

1.2.1 General Objective

Study on LTE PRB utilization prediction per frequency bands in Addis Ababa Ethio telecom sites and compares the performance of Prophet, LSTM, and XGBoost models.

1.2.2 Specific Objective

- Predict LTE resource utilization rate for LTE frequency bands in different time within certain Ethio telecom sites.
- Improve accuracy of resource utilization prediction using prophet model and compare with LSTM and XGBoost model.
- Prioritize the overloaded cells based on the future predicted resource utilization rate to balance the loads between the frequency layers.

1.3 Literature Review

Several recent studies have highlighted the potential of machine learning for predicting spectrum occupancy in cellular networks. Our thesis review the identified four particularly relevant papers that explore diverse techniques:

The study conducted in [2] investigated the use of time series forecasting techniques, including Autoregressive Integrated Moving Average (ARIMA) and Prophet, for predicting downlink throughput in LTE cellular networks in network dimensioning for the network planning team throughout the network design stage. The proposed system employs several KPIs to predict UE DL throughput . The paper utilizes metrics like MAE and RMSE to evaluate the prediction accuracy of both ARIMA and Prophet models. The paper reports that Prophet generally achieved lower MAE and RMSE values compared to ARIMA for the studied dataset. This suggests that Prophet was more effective in capturing the underlying trends and patterns in the DL throughput data. The paper highlights the limitations of statistical models like ARIMA in capturing highly non-linear relationships in the data.

In [3] Deep RL explored for predicting spectrum occupancy in cognitive radio networks. This method leverages time-based (temporal) and frequency correlations to predict spectrum usage changes. While promising for dynamic spectrum allocation, the high computational complexity of Deep RL training and the lack of comparison with other prediction techniques require further investigation. This research used historical data to predict spectrum occupancy conditions over a particular frequency range. RL algorithms used as a model. The paper demonstrates that the Deep RL approach can achieve accurate spectrum occupancy prediction by exploiting time and frequency correlations in real-world spectrum measurements. The paper focuses on real-world spectrum measurements, which may not be readily available in all LTE network management environments.

A study conducted in[4] proposed a hybrid approach that combines LSTMs, known for capturing temporal patterns, with an attention mechanism that focuses on crucial traffic-influencing features. This approach has the potential to outperform LSTMs, but details regarding the specific model architecture and the trade-off between accuracy and computational cost are not readily available. This paper proposes a hybrid approach for cellular network traffic prediction that combines an Attention-based LSTM (ALSTM) model with a statistical model. The ALSTM learns the temporal dependencies in traffic data, while the statistical model captures longterm trends. The hybrid model demonstrated superior prediction accuracy compared to standalone LSTM or statistical models. The attention mechanism helped focus on the most relevant past data points for improved prediction. The research focuses on predicting overall network traffic, and further investigation might be needed to isolate and predict PRB utilization specifically.

Machine learning for general cellular spectrum analysis in [5]. This approach can reveal insights into spectrum usage patterns, resource allocation strategies, and potential inefficiencies. However, the specific techniques employed and the potential applications of these findings for network optimization need further exploration. The research used the Rohde and Schwarz FSH6 Handheld Spectrum Analyser to measure frequency in the range of 100 kHz to 6 GHz and recorded in a Microsoft Excel sheet and developed a set data for Qasimabad region of Hyderabad city, Pakistan. after collecting the data,experimented with three types of machine algorithms, namely logistic regression, k-nearest neighbours and Naïve Bayes. The logistic regression model performs 94.93 percent in UAR and 95.80 percent on the test score. the K-NN classifier performs 78.11 percent on the validation partition and 82.00 percent for the test partition. the Naïve Bayes classifier achieves 88.11 percent for the validation and 92.02 percent for the test partition on UAR. This paper only uses data collected from indoor environments and analyses the expected results, so there is a lack of outdoor environment data, also due to their data collection methods, the data sets are insufficient in quality and in quantity.

By examining these diverse approaches and their limitations, our thesis review establishes a strong foundation for delving deeper into machine learning techniques for PRB utilization prediction in cellular networks. Our research aims to address the identified limitations and contribute to the ongoing advancements in this crucial area of network optimization.

1.4 Scope and Limitation

1.4.1 Scope

This thesis is focused on predicting future PRB utilization in LTE networks.We evaluated three models (Prophet, LSTM, XGBoost) using real-world data from Ethio Telecom. Sorting and prioritization algorithm developed to prioritize overloaded cells for improved load balancing.

1.4.2 Limitation

The models developed and evaluated may be specific to the characteristics of the Ethio Telecom network and its traffic patterns. Their generalizability to other LTE networks with different configurations or user behavior might require further adaptation.

1.5 Contribution

This thesis contributes to the field of LTE network optimization by exploring the application of machine learning for predicting future PRB utilization. By evaluating and selecting the most accurate prediction model, along with the development of sorting and prioritization algorithm, this thesis implemented a data-driven approach for identifying overloaded cells. This capability paves the way for implementing intelligent load balancing strategies, ultimately leading to more efficient resource allocation, reduced congestion, and a significantly enhanced user experience in LTE networks.

1.6 Thesis Organization

This thesis is organized into six chapters. The first Chapter is thesis introduction that introduces the problem of load imbalance in LTE networks, objectives and literature review. The second Chapter lays the foundation by explaining cellular network architecture, spectrum allocation in LTE, the concept of PRBs and the role of PRB utilization prediction in load balancing. The third Chapter dives into the details of the chosen machine learning models (Prophet, LSTM, XGBoost) for prediction. Chapter four presents overall methodology, data preprocessing and model building. Chapter five shows model evaluation result and the sorting and prioritizing algorithm. Finally, Chapter five concludes with the key findings and potential future research directions.

Chapter 2: Spectrum Allocation in Cellular Networks

2.1 Introduction

Cellular networks have become an indispensable part of modern life, enabling seamless voice communication, high-speed data access, and a multitude of other applications. The foundation for this ubiquitous connectivity lies in spectrum allocation, the process of dividing the limited radio frequency spectrum into designated bands for different wireless services. Efficient spectrum allocation is crucial for maximizing network capacity, minimizing interference, and ensuring the continued growth of mobile communication technologies. Regulatory bodies like the Federal Communications Commission (FCC) in the US or the European Telecommunications Standards Institute (ETSI) in Europe play a critical role in this process, meticulously assigning bands for various services – from cellular voice calls (governed by standards like global system for mobile communications(GSM) to mobile data access (facilitated by technologies like universal mobile telecommunications service(UMTS) and its successor, LTE [6] . Efficient spectrum allocation is paramount for maximizing network capacity. Imagine a highway with all lanes clogged by slow-moving vehicles. Similarly, inefficient allocation can lead to congestion, where multiple signals trying to occupy the same band interfere with each other, degrading call quality and data speeds. To address this challenge, a multifaceted approach is necessary. Techniques like frequency reuse allow for the same frequencies to be used in non-overlapping geographical areas, maximizing spatial efficiency[14].

Additionally, advancements in cellular network generations have enabled more flexible spectrum utilization. LTE, for instance, allows carrier aggregation(CA), where multiple non-contiguous frequency bands are combined to create wider channels, significantly increasing data capacity[15]. However, challenges persist. Static allocation strategies may not adapt well to dynamic traffic patterns, leading to underutilized resources in certain areas or times. Furthermore, spectrum fragmentation, where operators hold licenses in various non-contiguous bands, can add complexity to resource management. Fortunately, ongoing research offers promising solutions. Licensed Shared Access (LSA) techniques enable LTE to operate in spectrum bands shared with other services, promoting more efficient utilization [5]. Additionally, machine learning is making significant strides in optimizing resource allocation. Techniques like PRB utilization prediction can provide valuable insights into future network traffic demands, allowing operators to implement dynamic load balancing strategies within LTE networks [6]. As we move towards 5G and beyond, with even greater demands on network capacity, efficient spectrum allocation will remain a crucial cornerstone for ensuring seamless connectivity and enabling the development of innovative mobile services that shape our daily lives.

This chapter delves into the intricacies of spectrum allocation in cellular networks. The next sections explore various allocation techniques, analyze the challenges and opportunities associated with current practices, and shows emerging trends that shape the future of spectrum management.

2.2 Electromagnetic Spectrum and Radio Waves

The electromagnetic spectrum is a fundamental concept in physics encompassing a vast range of frequencies and their corresponding wavelengths. It acts as a carrier for various forms of energy, including radio waves, light, and X-rays. While the spectrum is vast, efficient utilization of a specific portion, the radio spectrum, is crucial for wireless communication technologies like cellular networks. The spectrum is categorized by frequency (measured in Hertz, Hz) or wavelength (measured in meters, m). These two quantities have an inverse relationship: higher frequencies correspond to shorter wavelengths, and vice versa. The following are a breakdown of some key regions of the electromagnetic spectrum[11].

Radio Waves (Lowest Frequencies/Longest Wavelengths): This portion of the spectrum, crucial for wireless communication, encompasses frequencies ranging from around 30 kHz to 300 GHz. Radio waves can travel long distances and penetrate obstacles reasonably well, making them ideal for applications like radio broadcasting, cellular networks, and satellite communication.

Microwaves: Microwaves occupy higher frequencies (up to 300 GHz) compared to radio waves. They are used in various applications like radar, microwave ovens, and Wi-Fi communication.

Infrared (IR): IR radiation lies beyond the visible range of light. It has applications in night vision devices, thermal imaging, and remote controls.

Visible Light: This narrow band of the spectrum is the portion of the electromagnetic spectrum that the human eye can perceive as colors, ranging from violet (highest frequency/shortest wavelength) to red (lowest frequency/longest wavelength).

Ultraviolet (UV): UV radiation has higher frequencies than visible light and is invisible to the human eye. It has applications in medical sterilization and industrial processes.

X-rays: X-rays possess even higher frequencies and shorter wavelengths than UV radiation. They are used in medical imaging for diagnostics.

Gamma Rays (Highest Frequencies/Shortest Wavelengths): Gamma rays are the most energetic form of electromagnetic radiation and are used in medical treatments and scientific research[9].

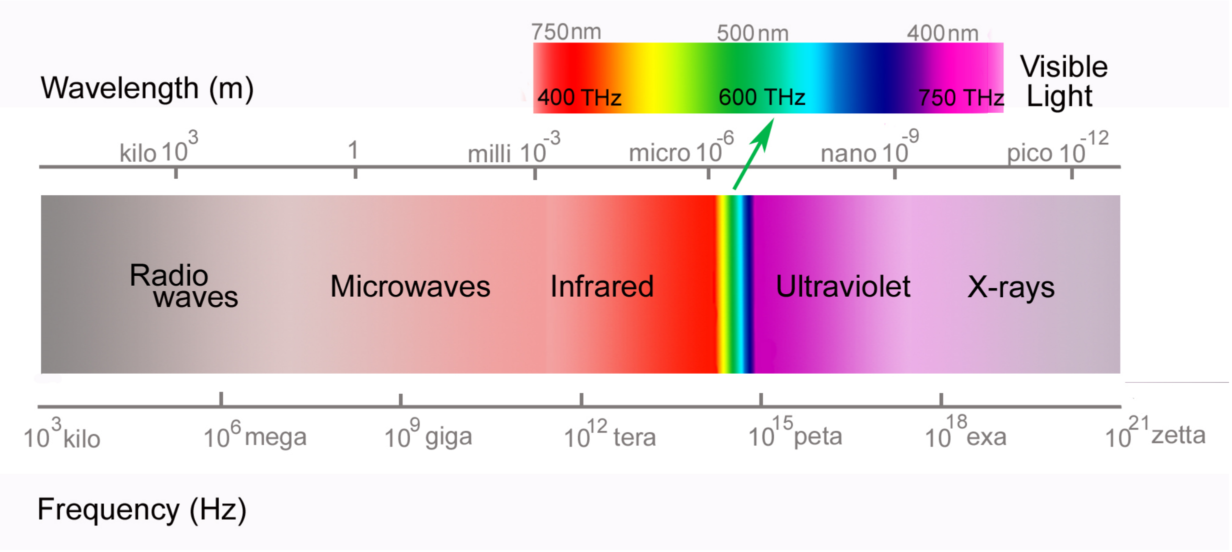


Figure 2.1: Electromagnetic Spectrum[36]

2.2.1 Spectrum Allocation and Its Importance

The radio spectrum, a valuable but finite resource, is essential for various wireless communication technologies. Regulatory bodies like the FCC in the US or ETSI in Europe play a critical role in spectrum allocation. They divide the radio spectrum into designated bands and assign licenses for specific services.

Techniques like frequency reuse and CA are employed to optimize spectrum utilization within cellular networks. However, challenges like static allocation strategies and spectrum fragmentation necessitate ongoing research and development of new approaches. Machine learning techniques, for instance, are being explored for dynamic load balancing and spectrum utilization prediction within cellular networks[13].

The electromagnetic spectrum encompasses a vast range of frequencies, from extremely low frequencies (ELF) used in power transmission to extremely high frequencies (EHF) utilized for satellite communication[10]. Radio waves, a subset of the electromagnetic spectrum, are particularly well-suited for wireless communication due to their ability to propagate through air with minimal attenuation. However, the available radio spectrum is a finite resource, and its efficient allocation is essential for maximizing network capacity and minimizing interference.

By understanding the electromagnetic spectrum and the importance of spectrum allocation, we can appreciate the foundation upon which wireless communication technologies operate and the ongoing efforts to ensure efficient and ever-evolving use of this limited resource.

2.2.2 Properties and Propagation of Radio Waves

Cellular networks rely on radio waves for seamless communication. These invisible messengers carry information between mobile devices and base stations, enabling voice calls, data access, and a multitude of applications. Understanding the properties and propagation characteristics of radio waves is fundamental to optimizing cellular network performance.

Key Properties of Radio Waves for Cellular Networks

(a) Frequency and Wavelength: Radio waves occupy the lowest frequencies and longest wavelengths within the electromagnetic spectrum. The radio spectrum relevant for cellular networks typically ranges from around 30 kHz to 300 GHz. Frequency (measured in Hertz, Hz) and wavelength (measured in meters, m) have an inverse relationship: higher frequencies correspond to shorter wavelengths, and vice versa. Cellular networks utilize various frequency bands depending on the desired coverage area and data rate[10].

(b) Line-of-Sight Propagation: Ideally, radio waves travel in straight lines. However, in real-world scenarios, obstacles like buildings and terrain features can affect their path. Line-of-sight propagation is preferred for reliable signal transmission, especially at higher frequencies.

(c) Path Loss: As radio waves travel, their signal strength weakens due to a phenomenon called path loss. This attenuation increases with distance and depends on the frequency of the radio wave. Higher frequency signals experience greater path loss compared to lower frequencies[14].

(d) Multipath Propagation: Radio waves can reflect off surfaces like buildings and mountains, creating multiple paths to the receiver. These multipath signals can arrive at the receiver with varying delays and phases, potentially causing signal distortion and fading. Techniques like diversity reception and channel coding are employed to mitigate the effects of multipath propagation[15].

(e) Penetration: Radio waves possess varying degrees of penetration capabilities. Lower frequency waves can penetrate obstacles like walls better compared to higher frequency waves. This property is crucial for providing coverage in indoor environments and rural areas.

2.2.3 Impact of Radio Wave Properties on Cellular Networks

The properties of radio wave significantly influence cellular network design and performance:

I. Frequency Selection: The choice of frequency band for a cellular network depends on the desired trade-off between coverage and capacity. Lower frequencies offer wider coverage but lower data rates, while higher frequencies provide higher data rates but with limited coverage area.

II. Cell Planning: Understanding path loss characteristics is essential for cell planning, which involves determining the placement and configuration of base stations to ensure adequate signal strength and minimize interference across the network.

III. Handoff Management: As mobile devices move between cells, radio wave propagation characteristics influence handoff procedures, ensuring seamless continuity of service during handover events.

2.3 Cellular Network Architecture

Cellular network has a well-defined architecture, with each component playing a crucial role in facilitating communication. This article delves into the core elements of a cellular network, focusing on their relationship to spectrum allocation.

Basic Components of a Cellular Network

Mobile Stations (MS): These are the user devices, such as smartphones and tablets, equipped with antennas and transceivers for communication with the network. MS communicate with the nearest base station using allocated radio frequencies within a specific cell.

Base Stations: Also known as cell sites, base stations act as gateways between mobile stations and the core network. Each base station covers a designated geographical area called a cell. Base stations are equipped with powerful antennas and transceivers for transmitting and receiving radio signals on designated frequencies allocated for that particular cell.

Cells: A cellular network is divided into smaller geographical areas called cells. These cells are typically hexagonal to promote efficient use of space and minimize interference between neighboring cells. The size of a cell can vary depending on factors like population density, terrain, and desired network capacity[15].

Cell Coverage and Spectrum Allocation

The concept of cells and their coverage areas is intricately linked to spectrum allocation in cellular networks.

(a) Frequency Reuse: A fundamental principle in cellular networks is frequency reuse. The same set of frequencies can be reused in non-overlapping geographical areas to maximize network capacity. Cells are carefully planned to ensure minimal co-channel interference, a phenomenon that occurs when mobile stations in different cells try to communicate on the same frequency. Efficient spectrum allocation strategies like frequency division multiple access (FDMA) and time division multiple access (TDMA) determine how frequencies are assigned to different cells within the network[14].

(b) Cell Size and Frequency Allocation: The size of a cell is often determined by the allocated frequency band. Lower frequency bands generally offer wider coverage areas due to lower path loss (signal attenuation) experienced by radio waves. However, their capacity for carrying data is limited. Conversely, higher frequency bands provide higher data rates but have smaller coverage areas due to greater path loss. Network operators strategically allocate spectrum bands to cells based on the desired balance between coverage and capacity in that particular area. For instance, densely populated urban areas might utilize higher frequency bands with smaller cells to cater to the high demand for data traffic, while rural areas might benefit from lower frequency bands with larger cells for wider coverage.

(c) Handoff and Spectrum Allocation: As mobile devices move between cells; they need to seamlessly switch from one base station to another to maintain connectivity. This process is called handoff. Spectrum allocation plays a crucial role in ensuring a smooth handoff experience. Ideally, mobile devices should handoff to neighboring cells using the same or compatible frequency bands to minimize disruptions during the transition. Precise coordination between base stations and efficient spectrum allocation strategies are essential for seamless handoff and uninterrupted communication[6].

The cellular network architecture, with its core components of mobile stations, base stations, and cells, forms the foundation for seamless mobile communication. Spectrum allocation strategies intricately tie into this architecture, ensuring efficient use of radio frequencies, maximizing network capacity, and minimizing co-channel interference.

2.4 Traditional Spectrum Allocation Strategies

Cellular networks rely on efficient spectrum allocation to accommodate a multitude of users and ensure seamless communication. Traditional Multiple Access techniques, such as FDMA, TDMA, and Code Division Multiple Access (CDMA), played a pivotal role in early cellular network generations and continue to influence modern systems like LTE. This section explores these traditional MA techniques, highlighting their functionalities, limitations, and relevance to LTE.

1. Frequency Division Multiple Access

FDMA divides the available spectrum into non-overlapping frequency channels. Each user is assigned a dedicated frequency channel for communication, similar to how multiple lanes on a highway allow for simultaneous traffic flow.

Limitations in LTE:

Spectral Inefficiency: FDMA requires strict frequency separation between channels to avoid interference. This can lead to underutilization of the spectrum, especially in scenarios with varying traffic demands across channels.

Limited Scalability: As the number of users increases, the available spectrum becomes fragmented with smaller channel allocations, ultimately limiting network capacity.

Complexity in Channel Allocation: Dynamic allocation of channels to accommodate varying user demands can be challenging in FDMA systems.

Relevance to LTE: While not the primary access method in LTE, FDMA principles are still relevant for specific applications within the LTE ecosystem.[15].

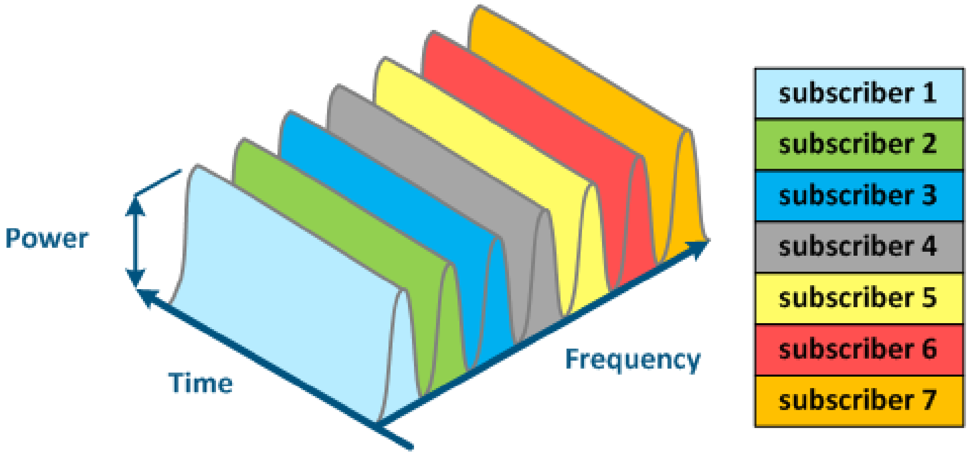


Figure 2.2: FDMA operation scheme[16]

2. Time Division Multiple Access

TDMA divides the available frequency channel into time slots. Each user is allocated specific time slots within the same frequency channel to transmit and receive data. This approach is akin to taking turns on a single lane, ensuring efficient utilization of the frequency resource.

Limitations in LTE:

Sensitivity to Delay: TDMA systems are susceptible to delays in the network, as missed time slots can lead to data loss. This becomes particularly critical for real-time applications like voice calls.

Limited Capacity for Bursty Traffic: TDMA struggles to efficiently handle situations with bursty traffic patterns, where users have varying transmission needs.

Complexity in Synchronization: Maintaining precise synchronization between users for accurate time slot allocation can be challenging in TDMA networks.

Relevance to LTE: Similar to FDMA, TDMA is not the core access method in LTE. However, some LTE functionalities, like GSM voice calls within the LTE network, might leverage aspects of TDMA for backward compatibility with legacy systems[6].

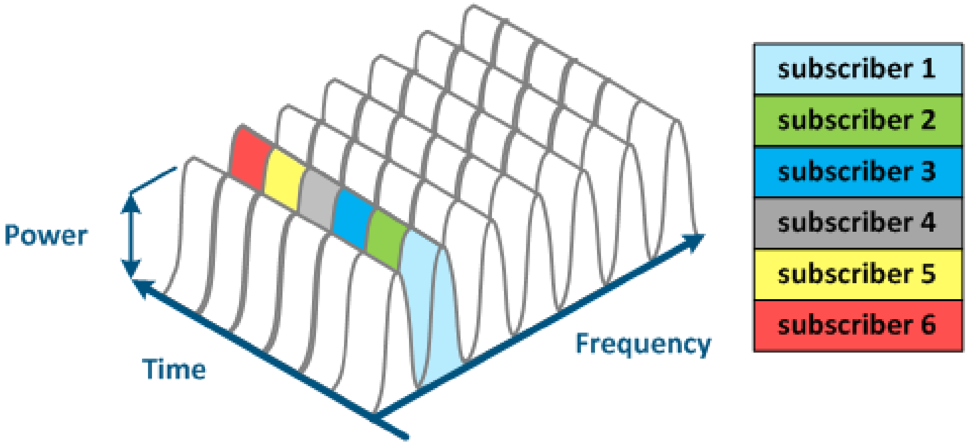


Figure 2.3: TDMA operation scheme[16]

3. Code Division Multiple Access

CDMA allows multiple users to share the same frequency channel simultaneously. Each user's signal is spread using a unique code sequence, enabling differentiation at the receiver. This is analogous to multiple conversations happening on the same channel but in different languages, where the receiver can decode the specific conversation intended for them.

Limitations in LTE:

Complexity and Increased Processing Power: CDMA systems require complex algorithms for signal spreading and decoding, leading to higher processing demands on user equipment(UE) and base stations.

Near-Far Problem: Signals from users closer to the base station can overpower those from users farther away. This phenomenon, known as the near-far problem, can degrade performance for users with weaker signal strengths.

Relevance to LTE: CDMA serves as the foundation for some legacy cellular network technologies (e.g., Wideband CDMA - wideband code division multiple access(WCDMA)). While not directly employed in core LTE access, the concept of spreading codes finds application in specific LTE functionalities like channel coding for error correction and user differentiation in certain scenarios[3].

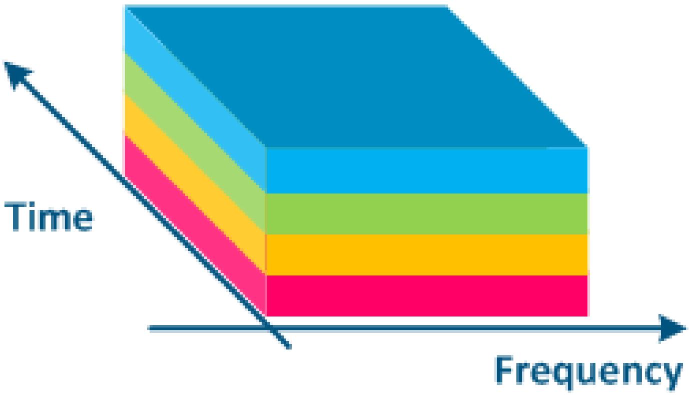


Figure 2.4: CDMA operation scheme[16]

Traditional MA techniques like FDMA, TDMA, and CDMA laid the groundwork for efficient spectrum allocation in cellular networks. While limitations exist, these techniques continue to influence modern systems like LTE in specific functionalities. As cellular networks evolve, advancements in access technologies like Orthogonal Frequency Division

Multiplex Access (OFDMA) employed in LTE offer greater flexibility and efficiency in spectrum utilization to cater to the ever-growing demands of mobile communication.

2.5 Spectrum Allocation for LTE

LTE , the core technology for 4G mobile networks, revolutionized cellular communication by offering significant advancements in data speed, capacity, and spectral efficiency compared to previous generations. This article delves into the spectrum allocation strategies employed in LTE, highlighting its advantages, spectrum bands, and innovative techniques like CA and OFDMA.

2.5.1 Advantages of LTE over Previous Generations in Spectrum Utilization

The followings are LTE advantages over previous generation.

1. Flexibility: LTE departs from rigid channel allocation schemes used in FDMA and TDMA. It utilizes OFDMA, a flexible access method that allows for dynamic allocation of resources (subcarriers) within a wider bandwidth. This enables efficient utilization of the spectrum based on real-time traffic demands[17].

2. Packet-Switched Architecture: LTE adopts a packet-switched architecture, unlike the circuit-switched approach used in earlier generations. This eliminates the need for dedicated channels for inactive users, leading to more efficient spectrum usage. Data is transmitted in packets, allowing for better resource allocation and improved network performance[18].

3. Advanced Modulation Techniques: LTE utilizes advanced modulation techniques like

Quadrature Amplitude Modulation (QAM) with higher order constellations (e.g., 64QAM) compared to previous generations. This allows for packing more data bits within the allocated spectrum, improving spectral efficiency[15].

4. Licensed Spectrum: LTE primarily operates on licensed spectrum. This means that regulatory bodies like FCC in the US or ETSI in Europe allocate specific frequency bands for exclusive use by LTE networks. This ensures predictable performance and minimizes interference from other services sharing the spectrum.

2.5.2 Frequency Ranges for LTE Deployments

LTE deployments utilize a variety of frequency bands, categorized as:

1. Low Bands (less than 1 GHz): These bands offer wider coverage areas due to lower path loss experienced by radio waves. However, they generally have lower data capacity.

2. Mid Bands (1-6 GHz): This range provides a good balance between coverage and capacity, making it suitable for dense urban environments.

3. High Bands (above 6 GHz): These bands offer exceptional data rates but have limited coverage area due to higher path loss. They are ideal for high-traffic areas and applications requiring ultra-fast speeds (e.g., 5G).

The specific frequency bands allocated for LTE deployments can vary depending on the region and regulatory guidelines.

Carrier Aggregation: Combining Spectrum for Increased Capacity. This technique allows an LTE network to combine multiple non-contiguous frequency bands into a wider logical channel, effectively increasing the available bandwidth and boosting data capacity [19].

2.5.3 Orthogonal Frequency Division Multiple Access

As mentioned earlier, OFDMA plays a crucial role in efficient spectrum utilization within LTE. Unlike traditional access methods that assign entire channels to users, OFDMA divides the available spectrum into smaller subcarriers. These subcarriers can then be dynamically allocated to different users based on their traffic demands. This allows for efficient resource allocation and improved network performance, especially in scenarios with varying user traffic patterns[20].

LTE's spectrum allocation strategies, with advantages like flexibility, packet-switched architecture, and advanced modulation techniques, have significantly improved spectral efficiency compared to previous generations. Licensed spectrum ensures predictable performance, while techniques like CA and OFDMA enable efficient resource utilization and cater to the ever-growing demands of mobile data traffic.

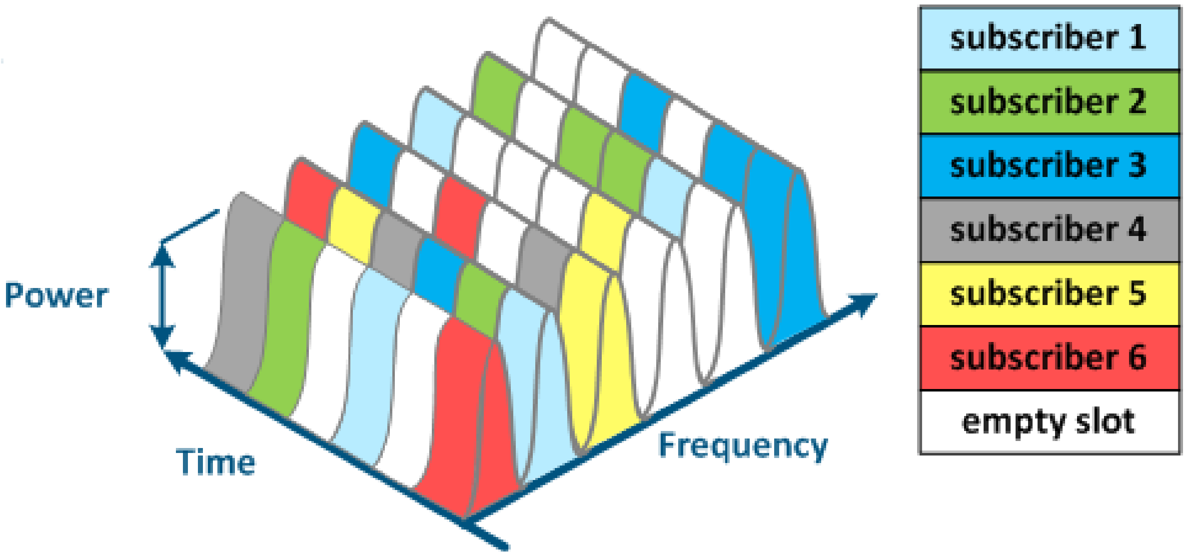


Figure 2.5: Orthogonal Frequency Division Multiple Access[16]

2.5.4 Challenges and Advancements in LTE Allocation

LTE revolutionized mobile communication, offering significant improvements in data speed and capacity. However, efficient spectrum allocation remains a critical challenge for maximizing network performance in LTE deployments. The following points explores the key challenges associated with spectrum allocation in LTE, along with potential solutions and future directions.

1. Static Allocation vs. Dynamic Traffic Patterns Challenge: Traditional spectrum allocation in LTE assigns specific frequency bands to cells in a static manner. This approach struggles to adapt to dynamic traffic patterns, where user demands fluctuate across time and geographical areas. Static allocation can lead to underutilized resources in areas with low traffic, while cells experiencing high traffic might suffer from congestion[21].

Potential Solutions:

LSA: This technique allows LTE to operate in spectrum bands shared with other services. When a band is unused by the primary service, LTE can utilize it dynamically, improving overall spectrum utilization.

Machine Learning for Load Balancing: Techniques like PRB utilization prediction can provide valuable insights into future network traffic demands. This information can be used for dynamic load balancing within the network, optimizing resource allocation across cells[22].

2. Spectrum Fragmentation: Managing a Patchwork of Frequencies Challenge: As operators acquire licenses in various frequency bands over time, their spectrum holdings can become fragmented, with non-contiguous bands spread across the spectrum. Managing these fragmented holdings can be complex, as efficient resource allocation requires careful

coordination across multiple bands[23].

Potential Solutions:

CA: This technique, discussed previously, allows combining non-contiguous bands into a wider logical channel, mitigating the limitations of fragmented spectrum holdings and improving overall network capacity.

Software-Defined Networking (SDN) and Network Function Virtualization (NFV): These emerging technologies offer greater flexibility in managing network resources. SDN can dynamically control resource allocation across the network, while NFV allows for virtualized network functions to be deployed on a shared infrastructure, potentially simplifying spectrum management across fragmented holdings[19].

3. Interference Challenge: Interference from other sources sharing the spectrum, such as Wi-Fi networks or legacy cellular systems, can disrupt LTE signals, degrading network performance and user experience. This is particularly challenging in densely populated urban environments with a high concentration of wireless devices[24].

Potential Solutions:

Advanced Interference Cancellation Techniques: LTE employs various techniques like frequency-domain scheduling and spatial filtering to mitigate the impact of co-channel and adjacent channel interference.

Cognitive Radio Approaches: Cognitive radio systems can dynamically sense the spectrum environment and adapt to identify and avoid interference sources, improving network performance[25].

While LTE has significantly improved spectrum utilization compared to previous generations, challenges like static allocation, spectrum fragmentation, and interference persist.

Ongoing research and development efforts explore solutions through dynamic spectrum management techniques, leveraging machine learning and emerging technologies like SDN and NFV. By addressing these challenges, network operators can optimize spectrum allocation and unlock the full potential of LTE networks, delivering a superior mobile broadband experience for users.

2.6 Load Balancing in LTE Networks

2.6.1 The Need for Load Balancing in LTE Networks

LTE networks have revolutionized mobile communication, enabling high data rates and a plethora of applications. However, ensuring a seamless user experience hinges on efficient network resource utilization. Uneven traffic distribution across cells can lead to congestion and performance degradation. This article explores the need for load balancing in LTE networks, highlighting the causes and consequences of imbalanced traffic and its impact on user experience.

I. Uneven Traffic Distribution: It is the Root of the Problem that causes Several factors contribute to uneven traffic distribution in LTE networks.

II. User Mobility: As users move around, traffic demands fluctuate across different cells. Densely populated areas or locations with high data usage activities (e.g., shopping malls, sporting events) will experience higher traffic compared to rural areas.

III. Hotspots: Certain locations, like business districts or transportation hubs, can become hotspots with concentrated user activity, leading to traffic overload within specific cells.

IV. Asymmetric Traffic Patterns: Mobile data traffic is often asymmetric, with uploads being significantly lower than downloads. This can lead to underutilized resources for uplink in some cells while the downlink experiences congestion.

Consequences of Imbalanced Traffic

(a) Network Congestion: Cells with high traffic loads become congested, leading to increased latency (delays), reduced data rates, and call drops for users within those cells. This creates a frustrating user experience.

(b) Resource Underutilization: Cells with low traffic experience under utilization of valuable resources like radio channels and bandwidth. This inefficiency translates to wasted network capacity[26].

(c) Increased Latency: Data packets experience longer delays as they queue for transmission on congested channels. This results in sluggish app performance, slow web browsing, and choppy video streaming.

(d) Reduced Data Rates: Congestion forces the network to reduce data rates for users in overloaded cells, hindering activities like downloading large files or video conferencing.

(e) Call Drops: In severe congestion scenarios, calls may be dropped entirely due to a lack of available resources to maintain the connection. These consequences can significantly impact user satisfaction and network performance metrics like QoS.

Uneven traffic distribution in LTE networks necessitates load balancing strategies. By proactively distributing traffic across cells and optimizing resource allocation, network operators can mitigate congestion, improve user experience, and ensure efficient utilization of network resources.

2.6.2 Introduction to Load Balancing Techniques in LTE Networks

The previous topic explored the challenges associated with uneven traffic distribution and network congestion in LTE networks. To ensure optimal performance and user experience, load balancing techniques are crucial.

Load Balancing:

Load balancing refers to the process of dynamically distributing traffic across various resources within a network. In the context of LTE networks, it aims to distribute user equipment traffic demands and channel utilization more evenly across cells to prevent congestion and optimize network performance.

Objectives:

Minimize Network Congestion: By distributing traffic across cells, load balancing techniques aim to prevent overloading specific cells, thereby minimizing delays, dropped calls, and reduced data rates for users.

Improve User Experience: Load balancing ensures a more consistent and improved user experience across the network by alleviating congestion and guaranteeing better service quality.

Enhance Resource Utilization: Efficient traffic distribution prevents under utilization of resources in low-traffic cells, maximizing the network's overall capacity[26].

Different Types of Load Balancing Strategies

LTE networks employ various load balancing strategies, categorized based on the scope of operation:

Inter-Cell Load Balancing: This strategy focuses on offloading traffic from overloaded cells to neighboring cells with available resources. Techniques like cell zooming, cell breathing, and inter-cell handover fall under this category.

I. Cell Zooming: This technique dynamically adjusts the coverage area of a cell based on traffic demands. During high traffic periods, the cell size shrinks to concentrate resources on a smaller area with more users, improving efficiency.

II. Cell Breathing: Similar to cell zooming, cell breathing dynamically adjusts the cell size but with a smoother transition. The cell expands or contracts based on traffic, ensuring a balance between coverage and capacity.

III. Inter-Cell Handover: When a UE moves from a congested cell to a neighboring cell with better signal strength and available resources, a handover occurs. This helps distribute traffic across the network.

Intra-Cell Load Balancing: This strategy focuses on optimizing resource allocation within a single overloaded cell. Techniques like user scheduling and power control fall under this category.

I. User Scheduling: The base station prioritizes UEs within a cell based on various factors like their channel conditions, queue lengths, and QoS requirements. This ensures efficient utilization of available resources within the cell.

II. Power Control: The base station dynamically adjusts the transmission power of UEs to manage interference and ensure fair allocation of resources across users within the cell.

Frequency Layer Load Balancing: This strategy leverages multiple frequency bands allocated to a cell. Traffic can be dynamically shifted between frequency bands based on congestion levels in each band.

Mode Selection: The network can choose between different transmission modes (e.g., Single Carrier-FDMA, Multi-Carrier FDMA) within a band based on traffic demands and channel conditions.

CA: As discussed earlier, CA allows combining non-contiguous frequency bands into a wider logical channel. Traffic can be distributed across these aggregated bands to optimize resource utilization.

Load balancing plays a critical role in ensuring efficient operation and optimal user experience in LTE networks. By employing various strategies like inter-cell, intra-cell, and frequency layer load balancing, network operators can dynamically distribute traffic, mitigate congestion, and maximize network capacity.

2.7 Physical Resource Block

In LTE networks, efficient resource allocation is paramount for ensuring optimal network performance and user experience. PRBs serve as the fundamental unit for allocating resources between the base station and UE. This article delves into the concept of PRBs, exploring their role, structure, and significance in LTE communication. PRB represents the smallest unit of resource allocation in the LTE air interface. It essentially combines two key dimensions of a radio signal: time and frequency.

(a) Time Domain: PRBs are allocated for a specific duration, typically corresponding to one-time slot within the LTE frame structure.

(b) Frequency Domain: Each PRB consists of a group of consecutive subcarriers within the overall system bandwidth. These subcarriers represent individual frequencies used for data transmission[27].

Structure and Size: The specific number of subcarriers included within a PRB can vary depending on the system bandwidth configuration. Typically, in most LTE deployments, a PRB comprises 12 contiguous subcarriers.

Resource Allocation: The base station dynamically allocates PRBs to UEs based on their traffic demands and channel conditions. This allocation process is crucial for efficient spectrum utilization and maximizing network capacity.

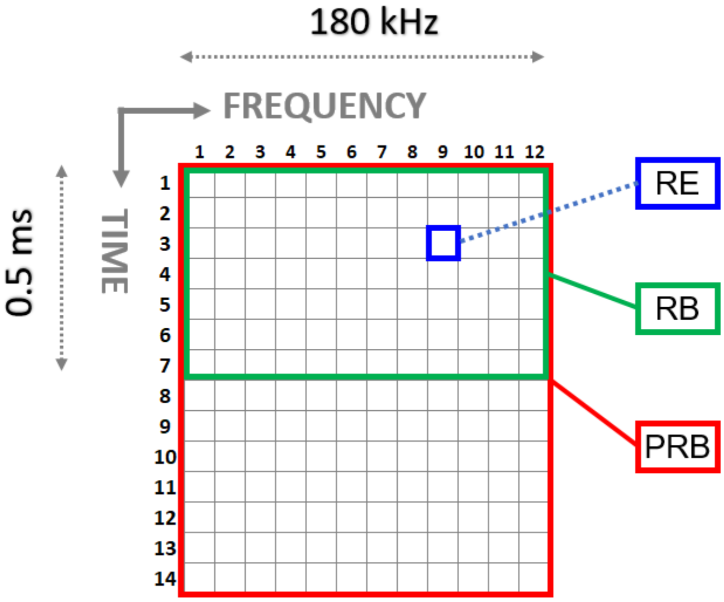


Figure 2.6: Physical Resource Block[28]

2.7.1 The Significance of PRBs in LTE Networks

Foundation for Data Transmission: PRBs represent the fundamental building blocks for transmitting data between the base station and UEs. By allocating appropriate PRBs based on channel quality and user demands, the network ensures reliable and efficient data transfer.

Enabling Flexibility: The ability to dynamically allocate PRBs allows the network to adapt to varying traffic patterns and user requirements. This flexibility is crucial for supporting diverse applications with different bandwidth needs, from real-time voice calls to high-speed data downloads.

Core for Load Balancing: Efficient load balancing across cells necessitates managing PRB allocation effectively. Techniques like cell zooming, inter-cell handover, and user scheduling all rely on strategic PRB allocation to distribute traffic and prevent congestion.

Advanced Techniques

I. PRB Bundling: In wider bandwidth deployments (e.g., LTE-Advanced), multiple PRBs can be bundled together to create even larger resource allocations for UEs with high data rate requirements.

II. PRB Scheduling: Advanced scheduling algorithms within the base station determine which UE receives which PRBs within a transmission frame. This scheduling process optimizes resource allocation based on various factors like channel quality, user priority, and traffic demands.

III. PRB Utilization Prediction: Machine learning techniques are increasingly used to predict future PRB demands within a cell. This proactive approach allows for resource reservation and optimized allocation strategies, enhancing network efficiency and user experience[1].

PRBs are the fundamental building blocks for resource allocation in LTE networks. Understanding their structure, significance, and role in various network operations is crucial for grasping the efficiency and flexibility of LTE communication. As LTE technology continues to evolve, advancements in resource allocation techniques and machine learning-based prediction will further optimize PRB utilization and ensure a seamless user experience in future cellular networks.

2.7.2 The Role of PRB Utilization Prediction in Load Balancing

PRB utilization prediction is revolutionizing load balancing strategies in LTE networks. By leveraging machine learning and historical data analysis, network operators can proactively manage resources, anticipate congestion, and optimize network performance. This approach ensures a superior user experience and maximizes the overall capacity of LTE networks. As technology evolves, advancements in machine learning and network intelligence will further enhance the accuracy and effectiveness of PRB utilization prediction, leading to even more efficient and dynamic load balancing in future cellular networks.

PRBs

In LTE networks, resources are allocated in units called PRBs. Each PRB represents a combination of time and frequency domain allocation, essentially a small time slot on a specific carrier frequency. These PRBs are the fundamental building blocks for transmitting data between the base station and UE.

Resource Allocation: The base station dynamically allocates PRBs to UEs based on their traffic demands and channel conditions. Efficient allocation ensures optimal network performance and user experience.

PRB Utilization Prediction: PRB utilization prediction aims to forecast future traffic demands and the corresponding PRB requirements within a cell or across multiple cells. This prediction capability empowers network operators to proactively manage resources and implement load balancing strategies before congestion occurs.

Role in Proactive Load Balancing: By anticipating future traffic demands, PRB utilization prediction enables several proactive load balancing strategies:

I. Resource Reservation: Based on predicted traffic surges, network operators can reserve specific PRBs in advance for high-demand areas or UEs with critical service requirements (e.g., emergency calls).

II. Inter-Cell Handover Initiation: Predicting congestion in a cell allows for initiating handover procedures for UEs to neighboring cells with available resources before significant delays or dropped calls occur.

III. Adaptive Modulation and Coding(AMC): Knowing future channel conditions and traffic demands, the network can adjust modulation and coding schemes to optimize resource utilization and cater to varying traffic patterns[29].

2.7.3 Techniques for PRB Utilization Prediction

Machine learning algorithms play a pivotal role in PRB utilization prediction. These algorithms analyze historical traffic data, cell configurations, and real-time network measurements to identify patterns and predict future traffic demands. Here are some common techniques:

Machine Learning for PRB Prediction

Optimizing resource allocation in LTE networks is essential for maximizing network performance and user experience. PRB utilization prediction, the ability to forecast future PRB demands within a cell, plays a critical role in proactive load balancing.

The Power of Machine Learning in PRB Prediction

Traditional traffic prediction methods often rely on statistical models that may struggle to capture the complex and dynamic nature of cellular network traffic. Machine learning offers a powerful alternative:

Data-Driven Approach: Machine learning algorithms can learn from historical traffic data, cell configurations, and real-time network measurements. This data provides valuable insights into traffic patterns and dependencies, enabling more accurate forecasts of future PRB requirements.

Adaptability: Unlike static models, machine learning algorithms can continuously learn and adapt to evolving traffic patterns. This adaptability is crucial for networks experiencing dynamic changes in user behavior and applications.

Suitable Machine Learning Algorithms for PRB Prediction

Several machine learning algorithms have demonstrated promising results for PRB utilization prediction:

Prophet: Facebook's Prophet algorithm is a valuable tool. Prophet is a time series forecasting model specifically designed to handle seasonality and holidays, which can be relevant factors influencing traffic patterns in cellular networks.

LSTM Networks: LSTMs are a type of recurrent neural network (RNN) particularly adept at capturing long-term dependencies in data. They can effectively analyze historical traffic patterns and predict future PRB demands by considering past trends and temporal relationships.

XGBoost: This powerful gradient boosting algorithm excels at handling complex data with various features. XGBoost can be trained on historical traffic data, cell configurations, and contextual factors like time of day or weather conditions to predict future PRB utilization with high accuracy.

Machine learning has emerged as a game-changer in PRB utilization prediction for LTE networks. By leveraging the power of Prophet,LSTM, XGBoost, and other suitable algorithms, network operators can gain valuable insights into future traffic demands. This proactive approach empowers them to implement effective load balancing strategies, optimize resource allocation, and ultimately deliver a superior user experience. As machine learning continues to evolve, even more sophisticated and accurate PRB prediction techniques are likely to emerge, further enhancing the efficiency and performance of future cellular networks.

2.8 Integrating PRB Prediction with Load Balancing in LTE Networks

Previous topics explored the significance of PRB prediction and the power of machine learning in forecasting future traffic demands within an LTE network. Here it delves into how PRB prediction can be integrated with various load balancing strategies to optimize network performance and user experience.

Leveraging Predictions for Smarter Resource Allocation

By leveraging PRB predictions, network operators can make informed decisions about resource allocation and proactively implement load balancing techniques before congestion occurs.

Inter-Cell Offloading: When PRB prediction indicates high traffic demands in a cell, the network can initiate offloading procedures. This involves strategically handing over UEs to neighboring cells with available resources, preventing congestion and ensuring smooth service continuity.

Intra-Frequency Adjustments: PRB prediction can guide adjustments within the same frequency band. If a particular subcarrier group within a cell is predicted to experience overload, the network can allocate UEs to different subcarrier groups with lower predicted utilization, distributing traffic more evenly within the available spectrum.

Cell Breathing Techniques: Cell breathing dynamically adjusts the coverage area of a cell based on traffic demands. PRB prediction allows for more proactive adjustments. When high traffic is predicted, the cell size can shrink to concentrate resources on a smaller area with more users, improving efficiency. Conversely, during low traffic periods, the cell can expand its reach.

Benefits of Integrating PRB Prediction and Load Balancing

Improved User Experience: Proactive load balancing based on PRB prediction minimizes congestion, leading to reduced latency, higher data rates, and fewer dropped calls, ultimately enhancing user experience.

Optimized Network Efficiency: By efficiently distributing traffic and preventing congestion, network operators can maximize capacity utilization and ensure optimal performance across the network.

Reduced Operational Costs: Efficient resource allocation and proactive management can minimize energy consumption and infrastructure requirements, leading to cost savings for network operators.

Integrating PRB prediction with load balancing strategies represents a significant advancement in LTE network management. By leveraging machine learning and predictive capabilities, network operators can optimize resource allocation, ensure a superior user experience, and unlock the full potential of their LTE networks. As technology evolves, further integration of artificial intelligence and real-time network data analysis will lead to even more sophisticated and dynamic load balancing techniques for future cellular networks.

Chapter 3: Basics of Machine Learning Algorithms

Machine learning is a subset of artificial intelligence that focuses on developing algorithms that enable computers to learn from and make decisions based on data. It involves the creation of models that can recognize patterns, make predictions, and improve their performance over time without being explicitly programmed to perform specific tasks. Unlike traditional software that relies on pre-defined instructions, machine learning algorithms can identify patterns and relationships within data sets. This allows them to make predictions or decisions for new, unseen situations. It can analyze vast amounts of data efficiently, capturing complex patterns and relationships. Machine learning models are exposed to more data, their performance typically improves. The continuous learning allows them to adapt to changing conditions and improve the accuracy of their predictions[30].

3.1 Machine Learning Algorithms

Machine learning algorithms are the backbone of machine learning models. They are designed to process data, recognize patterns, and make decisions or predictions. These algorithms can be broadly categorized into three types: supervised learning, unsupervised learning, and reinforcement learning.[31]

1. Supervised Learning: In supervised learning, the model is trained on a labeled dataset, which means that each training example is paired with an output label. The algorithm learns to map inputs to outputs and can predict the label of new, unseen data. Common supervised learning algorithms include:

- Linear Regression: Used for predicting a continuous value.
- Logistic Regression: Used for binary classification problems.
- Decision Trees: A tree-like model of decisions and their possible consequences.
- Support Vector Machines: Finds the hyperplane that best divides a dataset into classes.
- Neural Networks: Inspired by the human brain, they are used for complex pattern recognition tasks.

2. Unsupervised Learning: In unsupervised learning, the model is given data without explicit instructions on what to do with it. The goal is to find hidden patterns or intrinsic structures in the input data. Common unsupervised learning algorithms include:

- K-Means Clustering: Divides the dataset into K clusters, where each cluster contains similar data points.
- Hierarchical Clustering: Builds a tree of clusters based on the distance between data points.

- Principal Component Analysis: Reduces the dimensionality of the data while preserving as much variance as possible.
- Association Rules: Discovers interesting relations between variables in large databases.

3. Reinforcement Learning: In reinforcement learning, an agent learns to make decisions by performing actions in an environment to achieve a goal. The agent receives rewards or penalties based on the actions it takes and uses this feedback to improve its performance[32]. Key reinforcement learning algorithms include:

- Q-Learning: A model-free algorithm that learns the value of an action in a particular state.
- Deep Q-Networks: Combines Q-Learning with deep neural networks to handle large state spaces.
- Policy Gradient Methods: Learn policies that directly map states to actions by optimizing the expected return.

3.2 Machine learning Models for time series prediction

Time series prediction is a powerful technique for forecasting future values based on historical data. It involves analyzing sequences of data points ordered over time. By understanding the trends and patterns within this data, we can make informed predictions about what might happen next. The ability to predict future outcomes plays a critical role in various fields, from managing financial markets to optimizing energy consumption. Time series prediction emerges as a powerful tool in this endeavor, harnessing the power of historical data to forecast future values in sequences ordered over time. By uncovering the hidden patterns and relationships within such data, we can make informed predictions about their future behavior.

Time Series Data:

(a) Order matters: Unlike other data types, the order in which data points appear is crucial.[33].

(b) Different data types: Time series data can encompass various quantities like numerical values, categorical variables, or even text data.

(c) Frequency matters: The frequency at which data points are collected is important. It could be hourly, daily, monthly, quarterly, or even continuously recorded data.

Decomposition:

(a) Unveiling the hidden structure: Decomposition separates a time series into its fundamental components:

(b) Trend: Long-term upward or downward movement, representing the general direction of the series.

(c) Seasonality: Repetitive patterns within specific timeframes (e.g., weekly sales cycles, daily traffic fluctuations).

(d) Irregularity/Noise: Random fluctuations not captured by trend or seasonality, often attributed to chance events or external factors.

(e) Importance of each component: Each component plays a specific role in prediction. Trend captures the overall direction, seasonality helps account for recurring patterns, and noise needs to be considered for accurate estimates.

(f) Different decomposition methods: Various techniques exist, including moving averages, seasonal differencing, and statistical models like ARIMA.

Prediction Goal:

(a) Estimating the unknown: The ultimate aim is to predict future values based on the identified patterns and relationships within the historical data.

(b) Types of predictions: There are different types of predictions, such as point forecasts (single value), interval forecasts (range of possible values), and probabilistic forecasts (likelihood of different outcomes).

(c) Prediction horizon: The timeframe into the future for which we want to make predictions. The accuracy of predictions generally decreases as the horizon increases due to inherent uncertainties.

Essential Considerations:

(a)Stationarity: Ensuring data properties remain stable over time is crucial for many models.

(b)Model selection: Choosing the appropriate technique depends on data characteristics and prediction goals.

(c) Evaluation: Assessing prediction accuracy through metrics like Mean Squared Error(MSE) is essential.

(d) Limitations: Predictions are estimates, and inherent randomness can affect accuracy[33].

This thesis explores the potential of three prominent machine learning models – Prophet, LSTM, and XGBoost – for predicting PRB utilization in cellular networks. By delving into the strengths and weaknesses of each model, this work aims to establish a comprehensive framework for optimizing resource allocation and ensuring a seamless user experience.

3.2.1 Prophet Model

Prophet is a procedure for forecasting time series data based on an additive model in which nonlinear trends are adjusted for annual, weekly, and daily seasonality, plus holiday effects. It works best with time series that have strong seasonal effects and multiple seasons of historical data. Prophet is resilient to missing data and trend changes, and typically handles outliers well.[34]

Similar to a generalized additive model (GAM), with time as a regressor, Prophet fits several linear and non-linear functions of time as components. In its simplest form;

$$y(t) = g(t) + s(t) + h(t) + e(t) \tag{3.1}$$

g(t) - trend models non-periodic changes (i.e. growth over time)

s(t) - seasonality presents periodic changes (i.e. weekly, monthly, yearly)

h(t) - ties in effects of holidays (on potentially irregular schedules$\geq$ 1day(s))

e(t) - covers idiosyncratic changes not accommodated by the model

Trend (g(t)):

Can be represented as a series of connected linear segments with varying slopes between changepoints. Alternatively, non-linear functions like logistic growth or splines can be used.

Mathematically, it can be expressed as: Piecewise linear:

$$g(t) = \sum_{j} \beta_j max(0, t - \tau_j) \tag{3.2}$$

Logistic growth:

$$g(t) = L/(1 + exp(-k(t - m))) \tag{3.3}$$

Seasonality (s(t)): Represented by a sum of Fourier series terms for different frequencies (yearly, weekly, daily). Each term has specific amplitude and phase shift. Mathematically, it can be expressed as:

$$s(t) = \sum_{i} (a_i cos(2\pi f_i t + b_i)) \tag{3.4}$$

Holidays (h(t)): Can be modeled using pre-defined effects for known holidays or using custom regressors for other events. The specific mathematical form depends on the chosen approach[35].

Error Term (e(t)): Assumed to follow Gaussian distribution with heteroscedastic variance, allowing for varying error levels across the time series.

Mathematically, it can be expressed as:

$$e(t)\ (0, \sigma_t^2) \tag{3.5}$$

Bayesian Framework:

Prophet uses a Bayesian approach to estimate the parameters of the model. Prior distributions are placed on the parameters, reflecting prior knowledge about their expected values. Data likelihood is combined with the priors to obtain posterior distributions for the parameters. This allows for uncertainty quantification in the predictions through confidence intervals.

Changepoint Detection:

Prophet can automatically detect sudden shifts in the trend or seasonality using Bayesian techniques. This leads to more accurate predictions by capturing unexpected changes in the data. Prophet has core ideas and functionalities remain valuable for time series prediction. Prophet draws inspiration from GAMs, where the prediction is a sum of multiple smooth functions of different variables. In this case, time acts as the main regressor variable. It leverages Bayesian statistics for estimating parameters and quantifying uncertainty in predictions. It has the following key features.

- Automatic Feature Engineering: Handles seasonality, trends, and holidays automatically, simplifying the process.
- Robustness: Handles missing data, outliers, and trend shifts effectively.
- Interpretability: Provides interpretable insights into factors influencing predictions.
- User-Friendly: Easy to use with simple API and clear documentation.
- Bayesian Framework: Offers uncertainty quantification through confidence intervals.
- Change point Detection: Identifies sudden shifts in trends or seasonality[34].

. The prophet package leverages the power of PyStan, a Python library for performing Bayesian statistical analysis. While Prophet itself does not require explicit installation of PyStan, understanding their relationship is crucial for proper functionality and interpretability. PyStan Enables specifying statistical models in a high-level language, allowing for flexible modeling and efficient computation and utilizes Markov chain Monte Carlo (MCMC) algorithms to explore the posterior distribution of parameters, providing samples for inference and uncertainty quantification. It also Implements optimizations and parallelization techniques to handle large models and datasets efficiently.

Prophet's Reliance on PyStan:

I. Bayesian Framework: Prophet utilizes a Bayesian approach to estimate model parameters and quantify uncertainty in predictions. This requires performing posterior inference, where PyStan comes into play.

Posterior Sampling: PyStan implements efficient algorithms like MCMC to draw samples from the posterior distribution of parameters. These samples provide information about parameter values and their variability[35].

II. Uncertainty Quantification: Through posterior sampling, Prophet generates confidence intervals around predictions, reflecting the inherent uncertainty in future values.

3.2.2 LSTM Model

Long Short-Term Memory Networks is a deep learning, sequential neural network that allows information to persist. It is a special type of RNN which is capable of handling the vanishing gradient problem faced by RNN. Unlike traditional neural networks, LSTM incorporates feedback connections, allowing it to process entire sequences of data, not just individual data points. This makes it highly effective in understanding and predicting patterns in sequential data like time series, text, and speech.

The LSTM Cell: A Memory Champion: LSTM has unique architecture, with the crucial components being gates. Each cell holds not only the current input but also remembers essential information from the past, thanks to three carefully designed gates:

1. Forget Gate (f): This gate acts as a selective eraser, deciding which information from the previous cell state (long-term memory) is no longer relevant and should be forgotten. It takes the previous hidden state($h_(t-1)$)and current input x_t as input and uses a sigmoid function to output values between 0 and 1. Values closer to 1 indicate information worth keeping, while closer to 0 indicate forgetting[37].

$$f_t = \sigma(W_f * [h_(t-1), x_t] + b_f) \tag{3.6}$$

- Input:$h_(t-1)$(previous hidden state),x_t(current input)
- Activation function: Sigmoid σ
- Output:f_t(values between 0 and 1)
- W_f:weight matrix for forget gate
- b_f:bias vector for forget gate

2. Input Gate (i): This gate controls the flow of new information into the cell state. It also takes the previous hidden state and current input as input and uses a sigmoid function to determine which parts of the new information are important. Additionally,

it uses a hyperbolic tangent function to generate a candidate value, representing the new information to be added.

$$o_t = \sigma(W_o * [h_(t-1), x_t] + b_o) \tag{3.7}$$

$$h_t = o_t * tanh(C_t) \tag{3.8}$$

$w_o$weight matrix for output gate

$b_o$bias vector for output gate

- Input:$h_(t-1)$(previous hidden state),x_t(current input)
- Activation functions:$Sigmoid(\sigma)$for gate, tanh for processed cell state
- Outputs:o_t(gate values between 0 and 1),h_t(current hidden state)

3. Cell State (C): This is the core memory unit of the LSTM, where the actual long-term information is stored. It updates based on the previous cell state, forget gate output, and new information controlled by the input gate. The forget gate output multiplies the previous cell state, essentially forgetting some information, while the input gate output multiplies the candidate value, allowing the new information to enter. Finally, the sum of these two products becomes the new cell state.

$$C_t = f_t * C_(t-1) + i_t * \ C_t \tag{3.9}$$

4. Output Gate (o): This gate determines what information from the current cell state should be exposed as the output of the LSTM cell. It takes the previous hidden state

and current input as input and uses a sigmoid function to decide which parts of the cell state are relevant for the current time step. It then uses a hyperbolic tangent function to process the entire cell state, and the output gate's output multiplies this processed value, controlling the final information released as the hidden state(h_t).

$$o_t = \sigma(W_o * [h_(t-1), x_t] + b_o) \tag{3.10}$$

$$h_t = o_t * tanh(C_t) \tag{3.11}$$

w_o weight matrix for output gate

b_o bias vector for output gate

- Input: $h_(t-1)$(previous hidden state),x_t(current input)
- Activation functions: $Sigmoid(\sigma)$for gate, tanh for processed cell state
- Outputs: o_t(gate values between 0 and 1),h_t(current hidden state)

LSTMs are predominantly used to learn, process, and classify sequential data because these networks can learn long-term dependencies between data steps in time. Commonly LSTM is used in sentiment analysis, language modelling, speech recognition, and video analysis. it is explicitly designed to avoid the long-term dependency problem. Remembering information for long periods of time is pretty much their default behaviour, it's not something they have a hard time learning, but they do require more training data to learn effectively, and LSTMs can be slow to train on large data sets. This is due to the fact that they must learn the parameters of the LSTM cells, which can be computationally intensive. Finally, they may not work well with highly nonlinear or noisy data[37].

3.2.3 eXtreme Gradient Boosting

XGBoost,is a highly popular and powerful machine learning algorithm used for tasks like regression, classification, and ranking. It falls under the umbrella of gradient boosting, which iteratively combines weak learners like decision trees to create a strong final model[38].

Key strengths of XGBoost:

(I) Enhanced efficiency: Its implementation leverages efficient data structures and parallelization techniques, making it significantly faster than traditional gradient boosting algorithms.

High accuracy: It often achieves state-of-the-art results on various benchmarks, showcasing its effectiveness in real-world applications.

(II) Regularization capabilities: Built-in features like shrinkage and L1/L2 regularization prevent overfitting, leading to more robust and generalizable models.

Flexibility: Supports various objective functions (e.g., squared loss, logistic loss) and custom evaluation metrics, adapting to diverse problems.

Core mechanics:

(a) Weak learners: XGBoost typically uses decision trees as weak learners, building small individual trees in each iteration.

(b) Gradient boosting principle: At each step, a new tree is added that focuses on correcting the errors made by previous trees, aiming to improve the overall prediction.

(c) Loss function: XGBoost utilizes a second-order Taylor expansion of the loss function, leading to faster convergence and potentially better performance.

(d) Regularization: Incorporates both L1 and L2 regularization to penalize complex models and prevent overfitting[39].

XGBoost's success hinges on its efficient architecture and robust mathematical foundation.

Architecture:

Sequential-Parallel Hybrid:

- Sequential in the sense of adding weak learners iteratively.
- Parallel in computing internal calculations within each iteration, boosting efficiency.

Distributed Computing:

- Can be scaled across multiple machines for handling large data sets.

. Sparse Data Handling:

- Optimized for datasets containing many missing values.

. In-Memory Computing: Optimized for datasets containing many missing values.

- Stores data in memory for faster processing, but might require sufficient RAM.

Mathematical formulation of XG Boost model

Objective Function:

Combines loss function (evaluates prediction error) and regularization term (penalizes model complexity):

$$Objective(t) = Loss(t) + \Omega(f_t) \tag{3.12}$$

Loss(t): often squared error for regression, logistic loss for classification.

$\Omega(f_t)$: $L1/L2$ regularization based on model complexity.

Gradient Boosting:

Each iteration adds a new weak learner(f_t)focusing on minimizing the gradient of the objective function:

$$f_t = argmin_f \Omega(f_t + \alpha_t * g_t \tag{3.13}$$

g_t: negative gradient of the objective function (residuals).

α_t: learning rate controlling step size in each iteration.

Second-Order Taylor Expansion:

XGBoost approximates the objective function using a second-order Taylor expansion. This allows for faster optimization and potentially better performance than traditional gradient boosting. Tree-Based Weak Learners: XGBoost typically uses decision trees as weak learners due to their interpretability and efficiency. Other options like linear models can also be used[39].

Chapter 4: **Methodology**

This chapter outlines the research methodology employed in this thesis to apply machine learning techniques for predicting PRB utilization in LTE networks. The methodology can be broadly categorized into the following stages:

1. Literature Review: The research commenced with a comprehensive literature review to gain a thorough understanding of existing knowledge in the domain. This involved reviewing relevant academic papers, journals, articles, and books that explored the topics of load balancing in LTE networks. This included studies on various load balancing techniques, their limitations, and the challenges associated with dynamic traffic patterns. Machine learning for resource utilization prediction focused on research exploring the application of machine learning algorithms for predicting network traffic or resource utilization in LTE or similar communication networks. The review aimed to identify suitable machine learning models, their strengths, weaknesses, and potential adaptations for PRB utilization prediction. Review of performance evaluation metrics for prediction models identified relevant metrics commonly used to evaluate the accuracy and performance of machine learning models for prediction tasks. These metrics would later be used to assess the effectiveness of the chosen machine learning models for PRB utilization prediction in our thesis.

2. Data Collection: Real-world data was collected from the Ethio Telecom performance

report system. This system monitors a mature LTE network with over 1,000 base stations operating across various frequency bands (800 MHz, 1800 MHz, and 2600 MHz). The data encompassed a period of three months with hourly resolution, covering a total of more than 6,000 cells. This data provided a rich and comprehensive dataset for training and evaluating the machine learning models.

3. Data Preprocessing: The collected data underwent a rigorous preprocessing stage using Python's Pandas library. This stage aimed to ensure data quality and prepare it for machine learning model training. Preprocessing techniques specific to our data were employed, including:Visualizing the data distribution helped to identify potential anomalies, outliers, and trends. Missing Value Handling, which may have occurred due to cell outages or limitations of the centralized LTE controller, were addressed using appropriate techniques. These techniques could involve interpolation, deletion, or imputation based on specific data patterns and characteristics. New features relevant to the prediction task were potentially created based on existing features. Data Cleaning,Any remaining inconsistencies or errors were identified and corrected to ensure data integrity.

4. Model Development: Three prominent machine learning models were selected for evaluation: Prophet, Long Short-Term Memory (LSTM), and XGBoost. These models were chosen based on their suitability for time series forecasting PRB utilization prediction is a time series forecasting task. Models like Prophet and LSTM excel in capturing temporal patterns within data.Existing research exploring machine learning for network resource prediction in communication networks informed this selection. Diversity in model characteristics,Choosing models with different strength s and weaknesses allowed for a more comprehensive evaluation and a potentially more robust solution. Each model was then

individually trained using the preprocessed data. This involved parameter tuning to optimize model performance for our specific dataset and prediction task.

5. Model Evaluation: The performance of each trained model was evaluated using established metrics commonly used for time series forecasting tasks. These metrics included: Rsquared metric measures the proportion of variance in the target variable (future PRB utilization) explained by the model's predictions. A higher Rsquare value indicates better model fit and prediction accuracy. MAE represents the average difference between the predicted values and the actual PRB utilization values. A lower MAE value signifies higher prediction accuracy. These metrics were employed to compare the performance of each model and ultimately identify the model that yielded the most accurate and reliable predictions for future PRB utilization in our LTE network dataset.

6. Sorting and Prioritization Algorithm: Following the evaluation and selection of the best performing model for PRB utilization prediction, sorting and prioritization algorithm developed. This algorithm tackles the crucial task of identifying and prioritizing cellular network cells based on their predicted PRB utilization. This prioritization becomes crucial for implementing effective load balancing strategies. The algorithm takes as input the predicted PRB utilization values for all cells within the network, obtained from the chosen machine learning model. The algorithm sorts the cells in descending order based on their predicted PRB utilization values. Cells with higher predicted utilization will be placed at the top of the sorted list. This sorted list provides a clear prioritization of cells based on their predicted load. Cells at the top of the list are considered the most overloaded and require immediate attention for load balancing strategies. Resources can be dynamically allocated or offloaded from these cells to alleviate congestion and optimize the performance.

7. Result Analysis and Conclusion: Based on the evaluation metrics, the performance of each model was compared and analyzed. The model with the best combination of accuracy (high Rsquare) and low error (low MAE) would be considered the most suitable model for predicting PRB utilization in our specific LTE network scenario. The final stage involved drawing conclusions from the research findings. This included discussing the performance of the chosen machine learning model for PRB utilization prediction. Additionally, it would explore the implications of the chosen model for implementing load balancing algorithms and optimizing resource allocation in LTE networks. The potential avenues for future research also included.

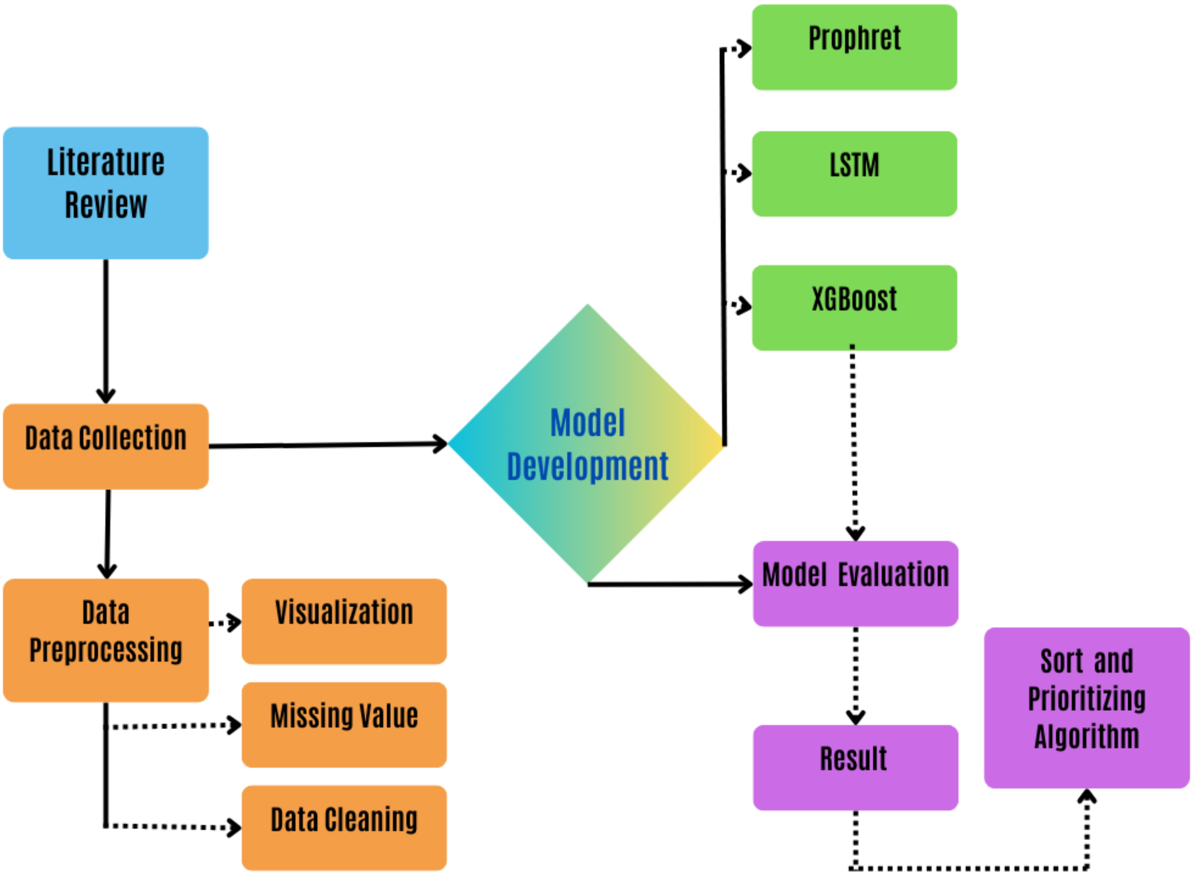
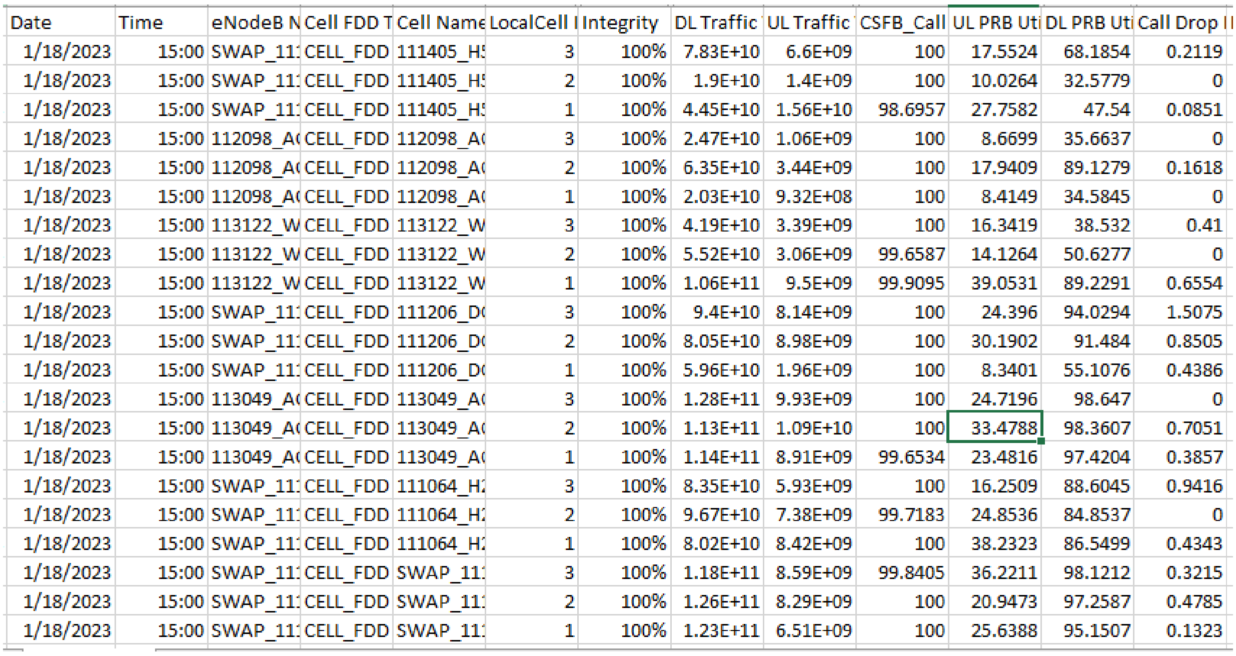


Figure 4.1: Overall Methodology.

4.1 Data Collection

Data for this study was collected from the Ethio Telecom performance report system, which monitors a mature LTE network with over 1,000 base stations spread across various locations within Addis Ababa. The data utilizes various frequency bands (800 MHz, 1800 MHz, and 2600 MHz) and this provides a diverse dataset, allowing to explore potential variations in PRB utilization across different bands. The data collected over a three-month period. The data offers a granular view of network performance by capturing information on an hourly basis. The data is initially extracted from the Ethio Telecom PRS in its raw form, likely stored as CSV files. This raw format provides flexibility for preprocessing and transformation before analysis. A sample of the historical data collected from Ethio Telecom, showcasing the various data points captured, is presented in Figure below.



Date	Time	eNodeB N	Cell FDD T	Cell Name	LocalCell I	Integrity	DL Traffic	UL Traffic	CSFB_Call	UL PRB Uti	DL PRB Uti	Call Drop I
1/18/2023	15:00	SWAP_11	CELL_FDD	111405_H	3	100%	7.83E+10	6.6E+09	100	17.5524	68.1854	0.2119
1/18/2023	15:00	SWAP_11	CELL_FDD	111405_H	2	100%	1.9E+10	1.4E+09	100	10.0264	32.5779	0
1/18/2023	15:00	SWAP_11	CELL_FDD	111405_H	1	100%	4.45E+10	1.56E+10	98.6957	27.7582	47.54	0.0851
1/18/2023	15:00	112098_A	CELL_FDD	112098_A	3	100%	2.47E+10	1.06E+09	100	8.6699	35.6637	0
1/18/2023	15:00	112098_A	CELL_FDD	112098_A	2	100%	6.35E+10	3.44E+09	100	17.9409	89.1279	0.1618
1/18/2023	15:00	112098_A	CELL_FDD	112098_A	1	100%	2.03E+10	9.32E+08	100	8.4149	34.5845	0
1/18/2023	15:00	113122_W	CELL_FDD	113122_W	3	100%	4.19E+10	3.39E+09	100	16.3419	38.532	0.41
1/18/2023	15:00	113122_W	CELL_FDD	113122_W	2	100%	5.52E+10	3.06E+09	99.6587	14.1264	50.6277	0
1/18/2023	15:00	113122_W	CELL_FDD	113122_W	1	100%	1.06E+11	9.5E+09	99.9095	39.0531	89.2291	0.6554
1/18/2023	15:00	SWAP_11	CELL_FDD	111206_D	3	100%	9.4E+10	8.14E+09	100	24.396	94.0294	1.5075
1/18/2023	15:00	SWAP_11	CELL_FDD	111206_D	2	100%	8.05E+10	8.98E+09	100	30.1902	91.484	0.8505
1/18/2023	15:00	SWAP_11	CELL_FDD	111206_D	1	100%	5.96E+10	1.96E+09	100	8.3401	55.1076	0.4386
1/18/2023	15:00	113049_A	CELL_FDD	113049_A	3	100%	1.28E+11	9.93E+09	100	24.7196	98.647	0
1/18/2023	15:00	113049_A	CELL_FDD	113049_A	2	100%	1.13E+11	1.09E+10	100	33.4788	98.3607	0.7051
1/18/2023	15:00	113049_A	CELL_FDD	113049_A	1	100%	1.14E+11	8.91E+09	99.6534	23.4816	97.4204	0.3857
1/18/2023	15:00	SWAP_11	CELL_FDD	111064_H	3	100%	8.35E+10	5.93E+09	100	16.2509	88.6045	0.9416
1/18/2023	15:00	SWAP_11	CELL_FDD	111064_H	2	100%	9.67E+10	7.38E+09	99.7183	24.8536	84.8537	0
1/18/2023	15:00	SWAP_11	CELL_FDD	111064_H	1	100%	8.02E+10	8.42E+09	100	38.2323	86.5499	0.4343
1/18/2023	15:00	SWAP_11	CELL_FDD	SWAP_11	3	100%	1.18E+11	8.59E+09	99.8405	36.2211	98.1212	0.3215
1/18/2023	15:00	SWAP_11	CELL_FDD	SWAP_11	2	100%	1.26E+11	8.29E+09	100	20.9473	97.2587	0.4785
1/18/2023	15:00	SWAP_11	CELL_FDD	SWAP_11	1	100%	1.23E+11	6.51E+09	100	25.6388	95.1507	0.1323

Figure 4.2: Sample of the historical data

4.2 Pre-Data Processing

The dataset encompasses data from over 6,000 individual LTE cells within the Ethio Telecom network. This vast amount of data allows us to capture the diverse behavior of PRB utilization across a large network segment.The study focuses on down link physical resource block(DL PRB) Utilization, which indicates the proportion of resources on the base station dedicated to transmitting data towards user devices. Analyzing this metric is crucial for understanding network capacity and potential bottlenecks. The data retrieved from the Ethio Telecom PRS system is in raw form. This format is not directly usable for training machine learning models. It necessitates preprocessing steps to transform the data into a suitable format for model input. Pandas offers various tools for data manipulation, cleaning, and feature engineering, which are likely employed in this thesis.

1. Feature Engineering:

This refers to the process of creating new features from existing data points. Visualization playing a role in feature engineering.

Visualization: Visualizing the time series data for each cell allows you to identify trends and seasonality in PRB utilization patterns. These patterns can be crucial for understanding network usage behavior over time and potentially incorporating them into the machine learning model.The provided graphs showcasing PRB utilization for various frequency bands reveal a significant difference in utilization rates across different bands and hours. This highlights an imbalanced load distribution that this research might address through specific techniques during model development.

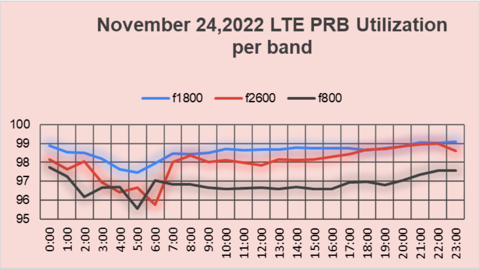


Figure 4.3: LTE PRB utilization per band

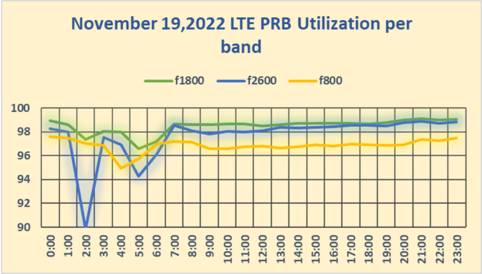


Figure 4.4: LTE PRB utilization per band

Day of Week: Extract this feature from the DateTime column to capture potential daily seasonality.

Hour of Day: This is likely already included, but explicitly separate it for analysis of hourly patterns.

Cell Grouping: consider grouping cells based on Cell names. This helped to identify trends and reduce the dimensionality of the data (useful for models sensitive to high dimensionality).

2. Data Cleaning:

The initial data might be spread across multiple CSV files, potentially representing data from different base stations or time periods. The preprocessing likely involves combining these individual CSV files into a single, unified dataset using Pandas functionalities. This allows for efficient analysis of all the collected data. Duplicate entries within a cell, characterized by identical timestamps, could indicate errors during data collection or storage processes. These duplicates can potentially skew the analysis of PRB utilization patterns. These duplicates can be flagged or removed entirely depending on the nature of the duplicates and the potential impact on the analysis. Removing duplicates ensure us analyze unique data points for each cell and time interval. This leads to a more accurate representation of PRB utilization patterns within the network. We have checked for duplicate timestamps within a cell, potentially caused by data collection errors. Removed duplicates as needed.

3. Replaces Missing Values:

The collected data contained missing values, primarily due to cell outages in the absence of a centralized LTE controller. To address this issue, a data imputation technique was employed. This technique leveraged the observed trend of similar network usage patterns on the same days of the week. Specifically, for missing hourly values, the corresponding values from the same day of the previous week were used. For missing daily values, the values from the previous day were used.

Missing Value Imputation:

The preprocessing likely involves techniques to address missing values within the data. This could involve strategies like data imputation (filling in missing values based on statistical methods or surrounding data points).

Last Week Same Day/Previous Day: This is a good initial approach, leveraging the inherent weekly trends that we identified from the data.

Interpolation: Use linear interpolation to fill gaps between existing data points within a reasonable timeframe (e.g., within the same day).

Missing value handling method

- A separate function replace missing values iterates through each row in the DataFrame.
- checked for missing or invalid ('/0') values in the 'DL PRB Utilization' column.

- If a missing value is found,attempts to find a replacement value by looking for:

- The same date and time from the previous week in the DataFrame.

- If not found, it looks for the same date and time from two weeks prior.

- If those fail, it checked for the previous day's data at the same time.

If a valid replacement value is found from any of these checks, it replaces the missing value in the current row.

4. Train-Test Split for Robust Model Evaluation

Dividing the data into separate training and testing sets is a crucial step in machine learning. It helps prevent overfitting, a phenomenon where a model performs well on the training data. The data was split into two sets: 80% for training the machine learning models and 20% for testing their performance. 80% of the data is allocated for training the machine learning model(s). This large portion allows the model to learn the underlying patterns and relationships within the data relevant to PRB utilization prediction. The training set plays a vital role in the learning process. The model is exposed to numerous examples of cell behavior, including variations in PRB utilization across different times and frequencies. By analyzing these, the model learns to identify these patterns and map them to the corresponding PRB utilization values. The remaining 20% of the data forms the testing set. This unseen data is critical for evaluating the model's generalizability. After training on the 80% portion, the model's performance is assessed on the testing set. This provides an unbiased estimate of how well the model can predict PRB utilization on new, unseen data, which is more representative of real-world network behavior.

Overall, in data pre procesing we have done cleaning and preparing the data for further analysis, specifically addressing missing values in the DL PRB Utilization column using a time-based lookback approach. It also lays the groundwork for potential future steps like grouping data by relevant features and potentially splitting it for large-scale processing.

4.3 Model Building

4.3.1 Prophet Model Building

Prophet is a probabilistic forecasting model specifically designed for time series data. It leverages a decomposable time series model with three main hyper parameters.

1. Changepoint Prior Scale

This hyperparameter controls the flexibility of the trend model. An important advantage of Prophet is its ability to automatically detect potential changes in the trend or seasonality of the data. This is crucial, as network traffic patterns might evolve over time due to factors like network upgrades, user behavior shifts, or introduction of new services. Prophet's ability to adapt to these changes leads to more robust predictions.

2. Seasonality Prior Scale

This hyperparameter controls the influence of the seasonality model. We configured the Seasonality prior scale parameter in the Prophet model to a value of 20. Realworld cellular network traffic often exhibits recurring patterns. Prophet can model these patterns, such as daily (higher utilization during peak hours), weekly (potentially lower utilization on weekends), or yearly (seasonal variations in user behavior). We incorporated these seasonal components, the model made more accurate predictions that account for these cyclical trends.

3. Holiday Prior Scale

This hyperparameter controls the influence of holidays on the predictions. Specific holidays or events can significantly impact network traffic patterns.We identified specific two holidays that could potentially influence the PRB utilization data in our dataset. This information was incorporated into the model by defining these holidays within a structured format, including their corresponding dates. Prophet with this necessary information account for potential spikes or dips in PRB utilization during these periods. This improves the model's ability to adapt to real-world network behavior.

Prophet Model Training

The training process for the Prophet model involved transforming the preprocessed data from multiple CSV files into a format suitable for analysis. This transformation combined data from various files into a single, unified dataset.

Crucially, for each unique cell within the network, the preprocessed data needed to be separated into two distinct components: timestamps and the corresponding DL PRB utilization values. Timestamps, encompassing both date and time information, provided the model with a crucial temporal context for the data. DL PRB utilization values, on the other hand, represented the actual measurements of resource utilization at the cell. These two components were then organized into separate columns within a data structure specific to each cell.

An important aspect of the training process involved creating a new Prophet model instance for each individual cell. This approach allowed the model to learn the unique characteristics of PRB utilization patterns at each location within the network. By analyzing the historical data for each cell, the model could identify trends, seasonal variations, and potential influences from holidays that might affect PRB utilization at that specific location. Essentially, the model underwent a training phase where it studied the cell's past utilization patterns to uncover underlying relationships and recurring behaviors. This training equipped the model to make informed predictions about future PRB utilization at each cell, taking into account the unique historical patterns observed at that location.

4.3.2 LSTM Model Building:Defining the Architecture

The LSTM model in this thesis is designed to predict DL PRB utilization in cellular networks.

Model Structure:

- The model is defined outside the loop iterating through cells. This means a single model instance is used and trained on data from each cell sequentially.

- The model takes an input layer that accepts sequences of data points. The specific format is (look_back, 24), where look_back represents the number of previous time steps used for prediction and 24 represents the number of features per time step (likely DL PRB utilization values for each hour).

- An LSTM layer with 64 units is used to capture temporal dependencies within the data. LSTM networks are adept at learning long-term relationships between data points, which is crucial for time series forecasting tasks like PRB utilization prediction.

- The return_sequences=False argument indicates that the LSTM layer only outputs the final hidden state, which summarizes the learned information from the entire sequence.
- A dense layer with one output neuron is added at the end. This layer maps the LSTM output (representing the learned patterns) to a single predicted DL PRB utilization value.

Model Compilation

- The model is compiled using the Adam optimizer, a popular optimization algorithm for training neural networks.
- The learning rate is set to 0.001, which controls how quickly the model adjusts its internal parameters during training.
- MSE is used as the loss function. This metric measures the average squared difference between the predicted and actual values. It helps the model learn to minimize this difference and improve prediction accuracy.
- MAE is included as an additional metric to monitor prediction accuracy. MAE represents the average absolute difference between predicted and actual values, providing another perspective on the model's performance.

LSTM Model Training: Optimizing the Model

The training process loops through each unique cell in the network. For each cell, a training dataset is created using a separate function. This function extracts sequences of past time steps (defined by look_back) from the cell's DL PRB utilization data and assigns the corresponding next value as the target label (the value to be predicted). A TensorFlow Dataset object is created and allowing the model to process the data in batches during training. The batch size is set to 16, which determines how many samples are processed together in each training step. All batches have the same size for efficient training.

Gradient accumulation is a technique we have employed to improve training stability, especially when dealing with limited graphics processing unit(GPU) memory. It involves accumulating gradients calculated over multiple batches before applying them to update the model's internal parameters. This can help address issues like exploding gradients that might occur with larger batch sizes. An accumulation_steps variable is set to 4, specifying the number of batches over which gradients will be accumulated. An Adam optimizer instance is created with a learning rate of 0.001.
The training process iterates through a predefined number of epochs which is 32 epochs. An epoch represents one complete pass through the entire training dataset. Within each epoch, the model iterates through batches in the training dataset. A gradient tape is used to record gradients during the forward pass of the model. The forward pass involves calculating the model's prediction for the current batch of data. The MSE loss is computed between the predicted and actual values. Gradients are calculated with respect to the loss using the gradient tape. Each gradient is divided by the accumulation_steps to account for the averaging effect during accumulation. The optimizer applies the accumulated gradients to update the model weights, essentially adjusting the model's internal parameters to improve predictions. After every accumulation_steps batches, the accumulated gradients are cleared using the optimizer, preparing for the next accumulation cycle.

Once the training process is completed, A prediction dataset is created from the future values using the same look_back window size as defined during training. This dataset essentially segments the future values into sequences suitable for feeding into the model for prediction.

Handles Prediction Length Mismatch: The number of predicted values not perfectly align with the number of future dates. This happened when the final prediction didn't fall exactly on an hourly boundary within the future date range. To address this the last look_back values are extracted from the future values as the new input. This new input is reshaped into a format suitable for the model. A new prediction is generated using the model and appended to the existing predictions array. This process ensures that all future dates have corresponding predictions.

Key Parameters

1. look_back: This parameter defines the number of previous time steps used for prediction. It influences the model's ability to capture historical patterns and make informed predictions. We have experimented with different values to find the optimal setting and 24 is suitable for our data.

2. Number of LSTM Units: The number of units in the LSTM layer which is 64 in our case that can determine the model's capacity to learn complex temporal relationships. Increasing units can improve model complexity but might also lead to overfitting. We have done tuning this parameter based on our data and computational resources and configured accordingly.

3. Learning Rate: The learning rate (0.001) controls how quickly the model updates its

weights during training. A lower learning rate can lead to slower convergence but might help prevent overfitting. We have Experimented with different learning rates to find a suitable value.

4. Batch Size: The batch size (32) determines how many samples are processed together during training. A larger batch size can improve training speed but might require more memory. A smaller batch size can lead to more frequent updates and potentially better convergence on smaller datasets. We have experimented with different batch sizes to find a balance between training speed and performance.

5. Gradient Accumulation: Gradient accumulation (with accumulation_steps) is a technique to improve training stability, especially when using a limited GPU memory. It allows for accumulating gradients over multiple batches before applying them to update the model weights. This can help address issues like exploding gradients that might occur with larger batch sizes.

6. Epochs: The number of epochs (32) specifies how many times the entire training dataset is passed through the model during training. Increasing epochs allows the model to learn more complex patterns but can also lead to over fitting if not carefully chosen. We Monitored the validation loss to identify the optimal number of epochs and decided the number of epochs.

7. Regularization: Dropout technique incorporated to prevent over fitting by randomly dropping neurons during training.

Hyperparameter Tuning: The key hyper parameters like look_back, number of LSTM units, learning rate,Epochs and batch size.

Table 4.1: LSTM Hyper Parameters

Parameters Name	Values
look_back	24
Number of LSTM Units	64
Learning Rate	0.001
Batch Size	32
Epochs	32

Optimization Techniques:

The optimal hyper parameter configuration will depend on our specific dataset and prediction task. We have experimented with the following techniques, evaluated the results using appropriate metrics, and refined the model iteratively for the best prediction performance on the data.

I. Monitor Training and Validation Loss: Track the training and validation loss during training. The training loss should generally decrease, while the validation loss should ideally stay flat or decrease slightly. A significant difference between the two might indicate over fitting.

II. Use Appropriate Evaluation Metrics: Choose evaluation metrics relevant to the prediction task. In this case, common metrics MSE is used,These measure the difference between predicted and actual values.

4.3.3 XGBoost Model Building: Defining the Architecture

XGBoost offers another approach to predicting Downlink PRB utilization in cellular networks. An XGBoost model is specifically designed for regression tasks (predicting continuous values) and is initialized using the xgb.XGBRegressor function. The followings are the key parameters that we used.

- n_estimators=300: This sets the number of decision trees (individual learners) used in the ensemble model. We have experimented different values and we found optimal number that balances accuracy and complexity.
- learning_rate=0.1: This controls how much the model updates its weights during each training iteration. The value we have set helps to prevent overfitting.
- reg:squarederror: This specifies the objective function used for training. reg:squarederror indicates that the model minimizes the MSE between predicted and actual values.

Table 4.2: XGBoost Hyper Parameters

Parameters Name	Values
n_estimators	300
learning_rate	0.1

XGBoost Model Training

The XGBoost model train the prepared data for the current cell group. During training, the model learns the relationship between the historical DL PRB Utilization values (features) and the actual values (target) to predict future values.

Creating Training and Target Data: Prepare the training data and target data for the current cell group. It extracts the DL PRB Utilization values. The created dataset iterates through the cell's DL PRB Utilization values, considering the specified look_back parameter. For each sample (time step), it creates a row in the train data. This row includes the look_back previous DL PRB Utilization values as features. The corresponding actual DL PRB Utilization value for the current time step is added to the target data. Once the XGBoost model is trained for each cell group,The future dates for which predictions are desired are defined. This involves creating a series of dates starting from a specified start date and spanning with hourly intervals. The trained XGBoost model is used to generate predictions for the future_dataset. The model leverages the learned patterns from historical data to forecast the DL PRB Utilization values for the specified future dates.

Chapter 5: **Result and Discussion**

5.1 System Model

This system model is representing three machine learning models Prophet, LSTM and XG Boost. the model is building to fit the data set well and better for the dataset behavior. Leveraging the strengths of Prophet, LSTM, and XGBoost for individual predictions. This system model allows to choose the best model for the time series data, ensuring accurate and adaptable predictions.

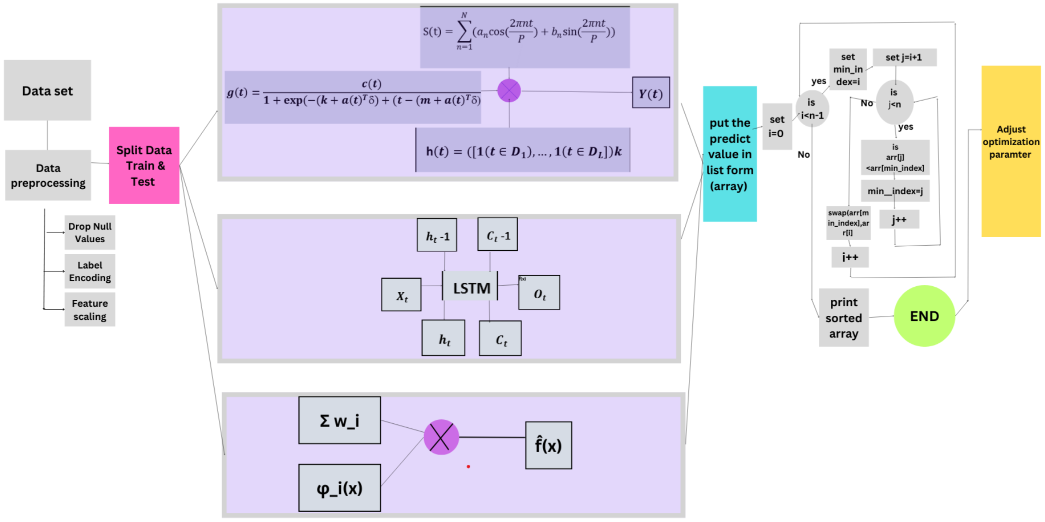


Figure 5.1: System Model.

5.2 Prediction Results using the three models

This thesis investigated the effectiveness of three machine learning models for predicting Downlink PRB utilization in cellular networks at the cell level. The ultimate goal is to leverage these predictions to achieve balanced cell loads across the network, optimizing resource allocation and network performance.

5.2.1 Prediction Result Using Prophet Model

Prophet model forecasting time series data based on an additive regression model, in this work the model fit nonlinear trends with hourly, and daily seasonality, plus holiday effects. The Prophet function of the prophet library is used to create the model. Predicted parameter values can be found using the prediction model method, with a data frame of time stamps corresponding to the prediction horizon as input. The results of the Prophet model's predictions are visualized in figures below.

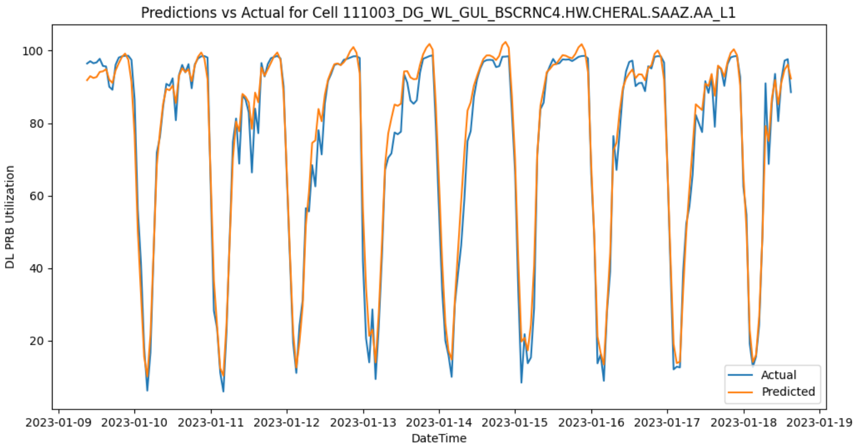


Figure 5.2: Cell 111003 L1 Actual Vs Predicted.

Evaluation for cell 111003 DG WL GUL BSCRNC4.HW.CHERAL.SAAZ.AA L1:

MAE: 3.3197

R squared: 0.9762

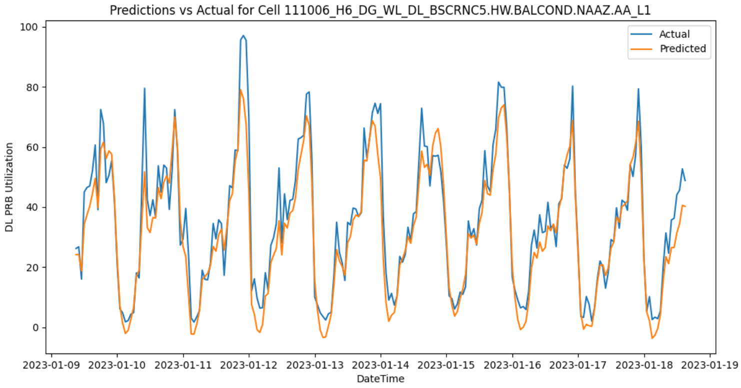


Figure 5.3: Cell 111006 L1 Actual Vs Predicted.

Evaluation for cell 111006 H6 DG WL DL BSCRNC5.HW.BALCOND.NAAZ.AA L1:

MAE: 5.4039

R-squared: 0.8961

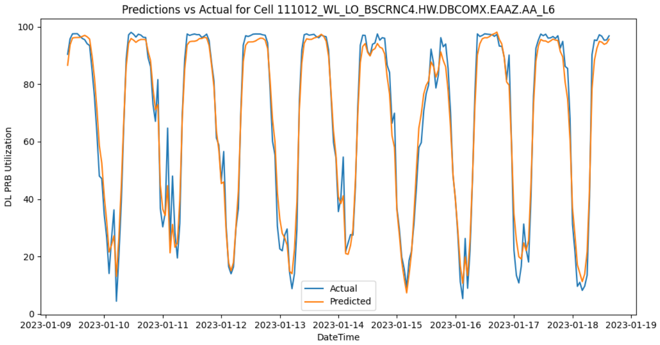


Figure 5.4: Cell 111012 L6 Actual Vs Predicted.

Evaluation for cell 111012 WL LO BSCRNC4.HW.DBCOMX.EAAZ.AA L6:

MAE: 3.7722

R-squared: 0.9756

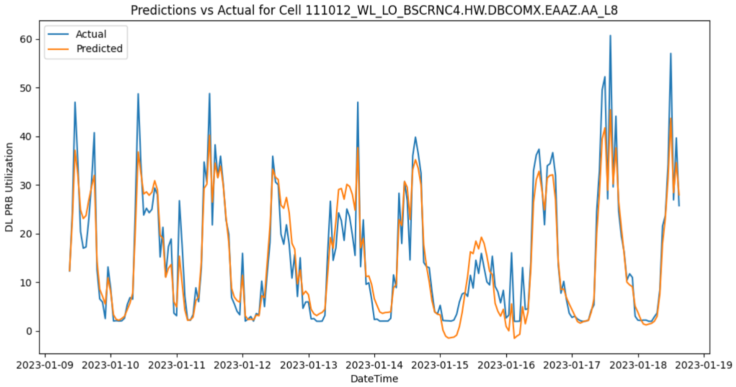


Figure 5.5: Cell 111012 L8 Actual Vs Predicted.

Evaluation for cell 111012 WL LO BSCRNC4.HW.DBCOMX.EAAZ.AA L8:

MAE: 3.0675

R-squared: 0.9029

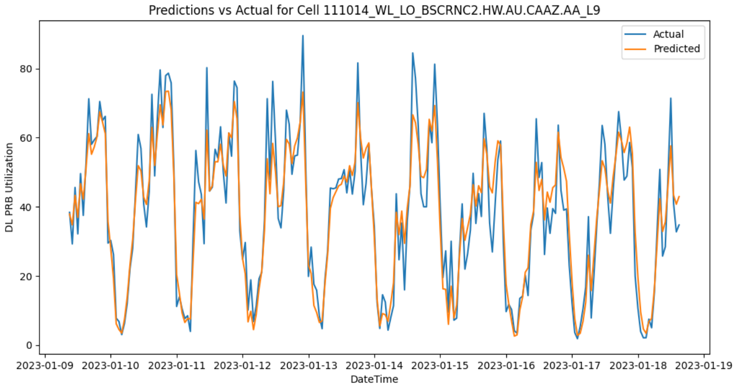


Figure 5.6: Cell 111014 L9 Actual Vs Predicted.

Evaluation for cell 111014 WL LO BSCRNC2.HW.AU.CAAZ.AA L9:

MAE: 5.1200

R-squared: 0.9081

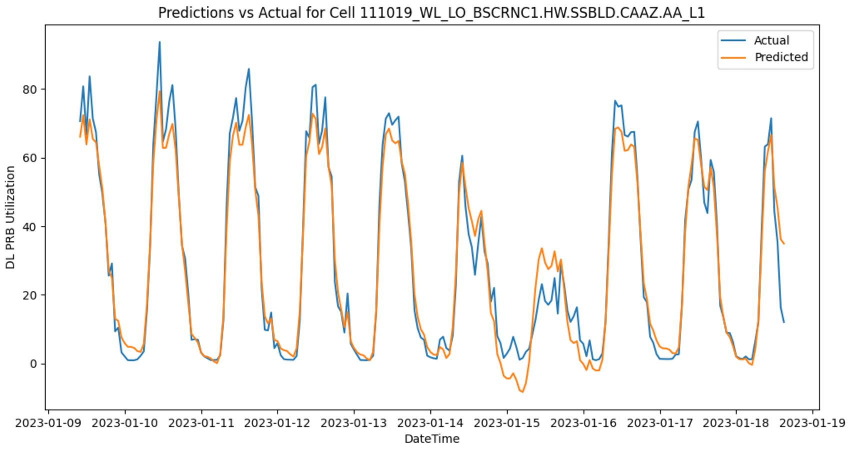


Figure 5.7: Cell 111019 L1 Actual Vs Predicted .

Evaluation for cell 111019 WL LO BSCRNC1.HW.SSBLD.CAAZ.AA L1:

MAE: 4.1510

R-squared: 0.9603

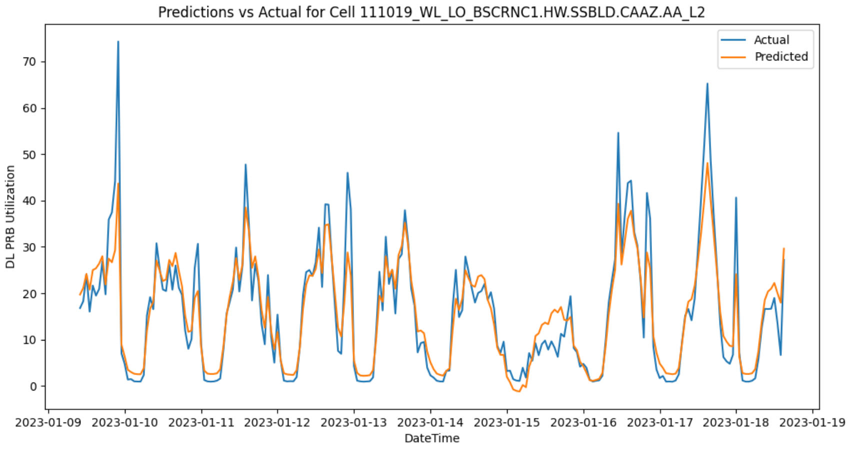


Figure 5.8: Cell 111019 L2 Actual Vs Predicted .

Evaluation for cell 111019 WL LO BSCRNC1.HW.SSBLD.CAAZ.AA L2:

MAE: 3.2551

R-squared: 0.8699

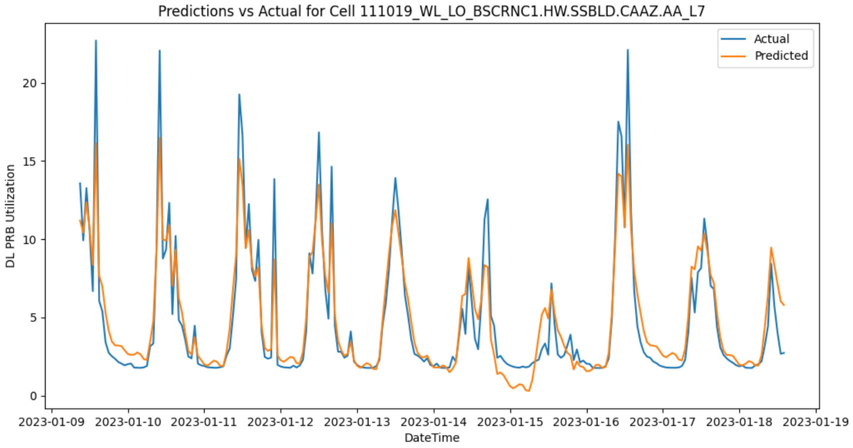


Figure 5.9: Cell 111019 L7 Actual Vs Predicted.

Evaluation for cell 111019 WL LO BSCRNC1.HW.SSBLD.CAAZ.AA L7:

MAE: 0.9916

R-squared: 0.8838

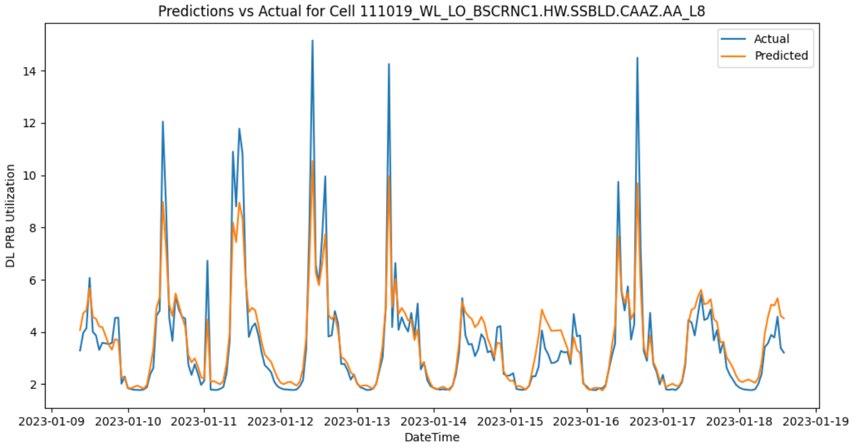


Figure 5.10: Cell 111019 L8 Actual Vs Predicted.

Evaluation for cell 111019 WL LO BSCRNC1.HW.SSBLD.CAAZ.AA L8:

MAE: 0.5267

R-squared: 0.8518

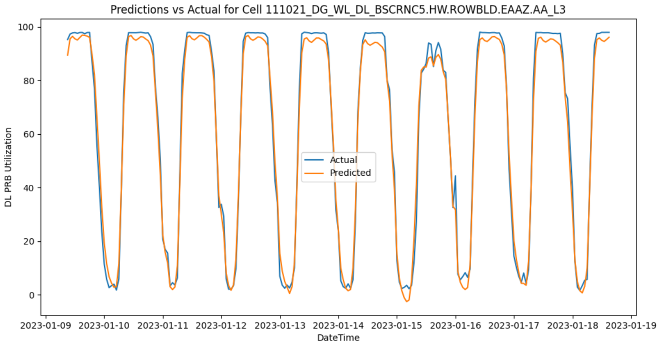


Figure 5.11: Cell 111021 L3 Actual Vs Predicted.

Evaluation for cell 111021 DG WL DL BSCRNC5.HW.ROWBLD.EAAZ.AA L3:

MAE: 3.1094

R-squared: 0.9901

Prophet Model Result Summary

The provided results offer valuable insights into the performance of the Prophet model for predicting Downlink PRB utilization in cellular networks. The 10 cells presented here are a random sample chosen from a larger dataset to illustrate the model's performance across various cell characteristics. The graphs for each cell visualize the actual and predicted PRB utilization values over time. The model effectively captures seasonal variations in traffic patterns like hourly and daily cycles. The predicted values align with the actual trends in the data.The evaluation process for the prophet model involved metrics like MAE or RMSE. R-squared indicates how well the model captures the variance in the actual PRB utilization data, while MAE reflects the average difference between predicted and actual values. Analyzing these metrics across different cells can provide insights into the overall accuracy of the model's predictions. The provided results show a range of MAE values across different cells from 0.5267 to 5.4039. The R-squared values in the results are generally high (mostly above 0.85), indicating that the Prophet model effectively captures the underlying trends and patterns in the PRB utilization data for most cells.

5.2.2 Prediction Result Using LSTM model

The LSTM model was employed to predict DL PRB utilization for individual cells within the cellular network. To assess the model's effectiveness, metrics like R-squared and MAE were used. The key to understanding the LSTM model's performance lies in the provided graphs. These visualizations offer valuable insights into how well the model predicts PRB utilization for each cell.

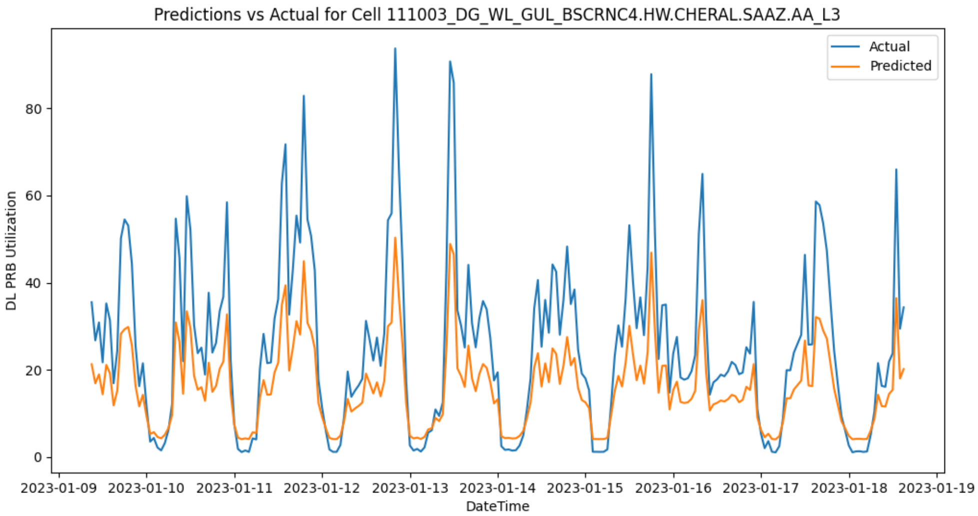


Figure 5.12: Cell 111003 L3 Actual Vs Predicted.

Evaluation for cell 111003 DG WL GUL BSCRNC4.HW.CHERAL.SAAZ.AA L3:

MAE: 10.2177

R-squared: 0.5207

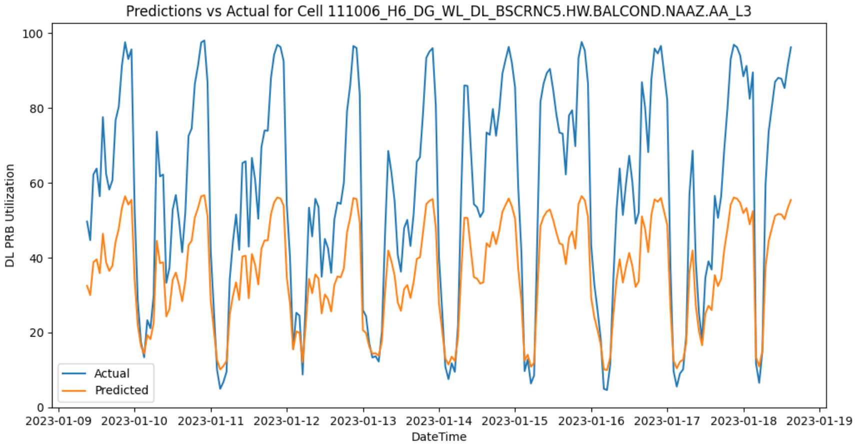


Figure 5.13: Cell 111006 L3 Actual Vs Predicted.

Evaluation for cell 111006 H6 DG WL DL BSCRNC5.HW.BALCOND.NAAZ.AA L3:

MAE: 21.7172

R-squared: 0.1901

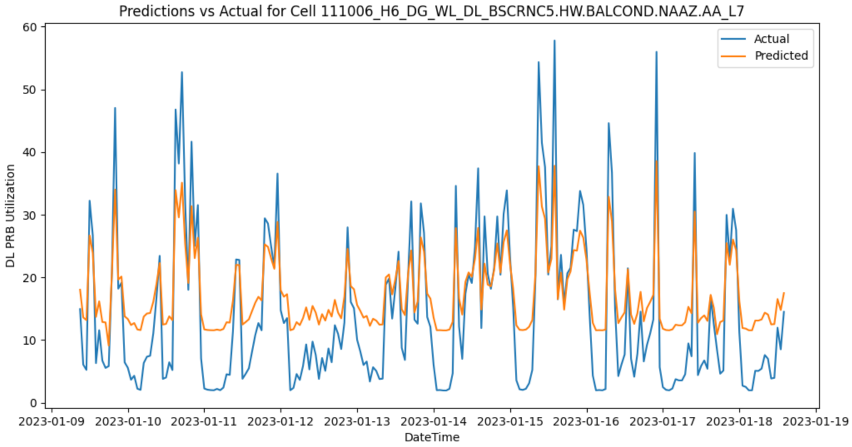


Figure 5.14: Cell 111006 L7 Actual Vs Predicted.

Evaluation for cell 111006 H6 DG WL DL BSCRNC5.HW.BALCOND.NAAZ.AA L7:

MAE: 6.2027

R-squared: 0.6616

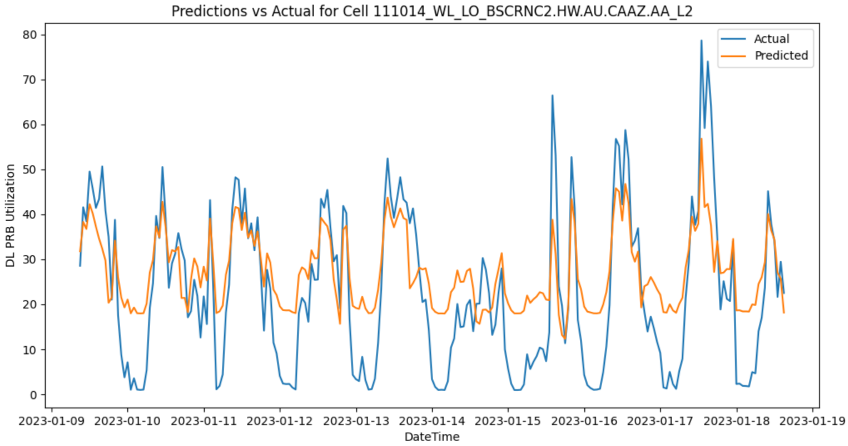


Figure 5.15: Cell 111014 L2 Actual Vs Predicted.

Evaluation for cell 111014 WL LO BSCRNC2.HW.AU.CAAZ.AA L2:

MAE: 9.6690

R-squared: 0.5650

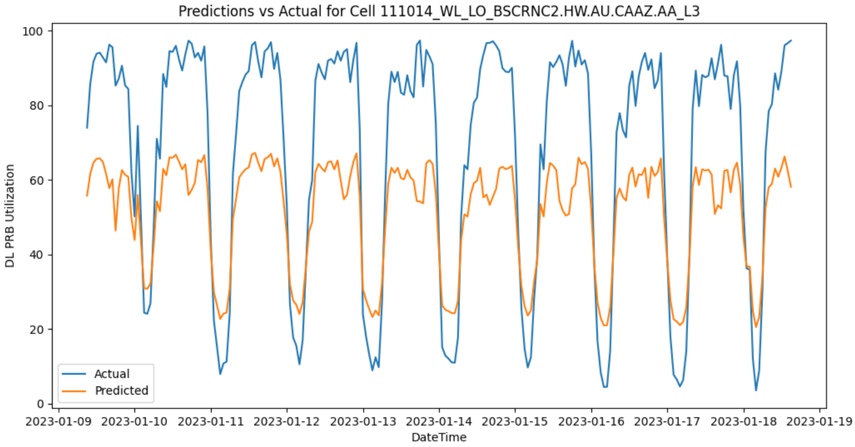


Figure 5.16: Cell 111014 L3 Actual Vs Predicted.

Evaluation for cell 111014 WL LO BSCRNC2.HW.AU.CAAZ.AA L3:

MAE: 21.5887

R-squared: 0.4044

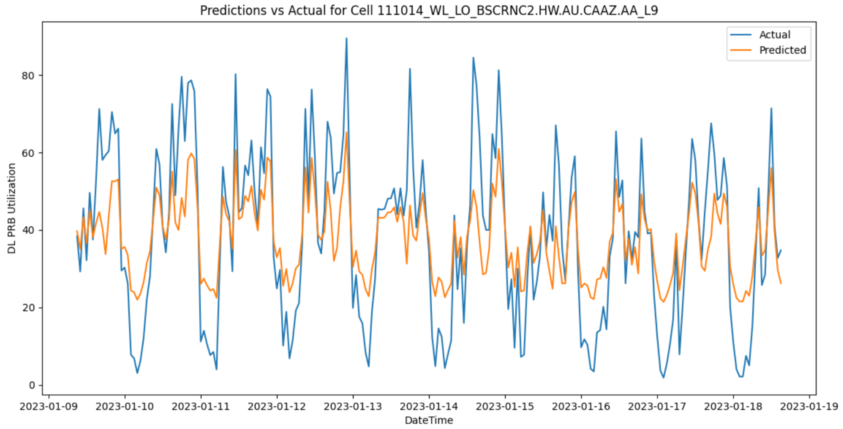


Figure 5.17: Cell 111014 L9 Actual Vs Predicted.

Evaluation for cell 111014 WL LO BSCRNC2.HW.AU.CAAZ.AA L9:

MAE: 10.6214

R-squared: 0.6395

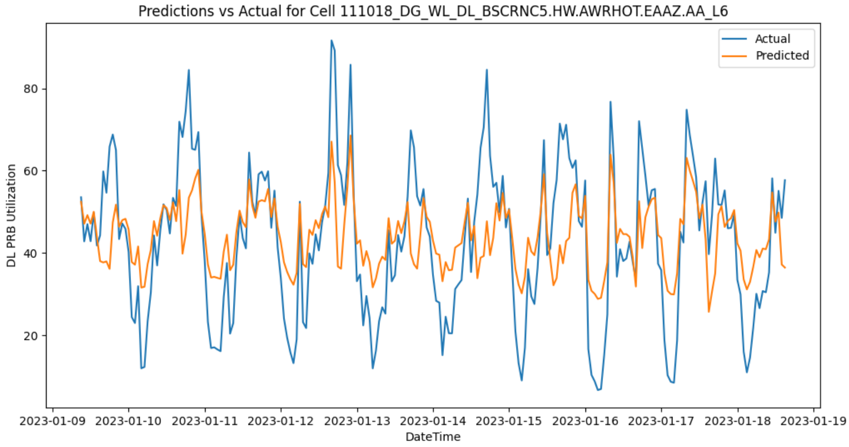


Figure 5.18: Cell 111018 L6 Actual Vs Predicted.

Evaluation for cell 111018 DG WL DL BSCRNC5.HW.AWRHOT.EAAZ.AA L6:

MAE: 10.7994

R-squared: 0.4458

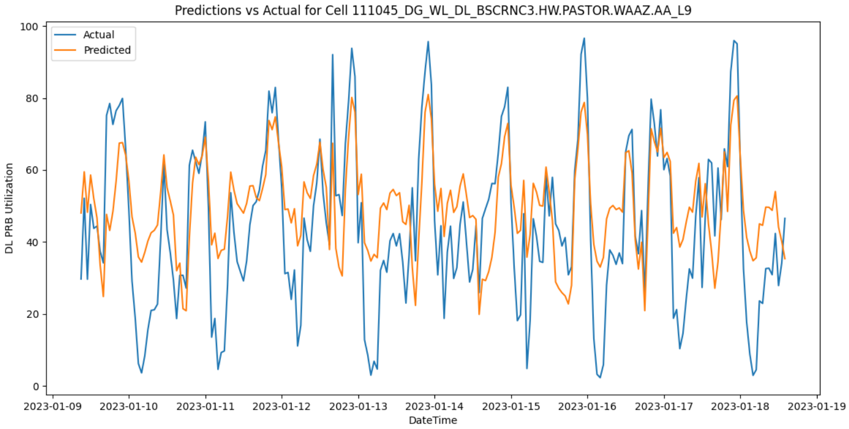


Figure 5.19: Cell 111045 L9 Actual Vs Predicted.

Evaluation for cell 111045 DG WL DL BSCRNC3.HW.PASTOR.WAAZ.AA L9:

MAE: 14.3418

R-squared: 0.4528

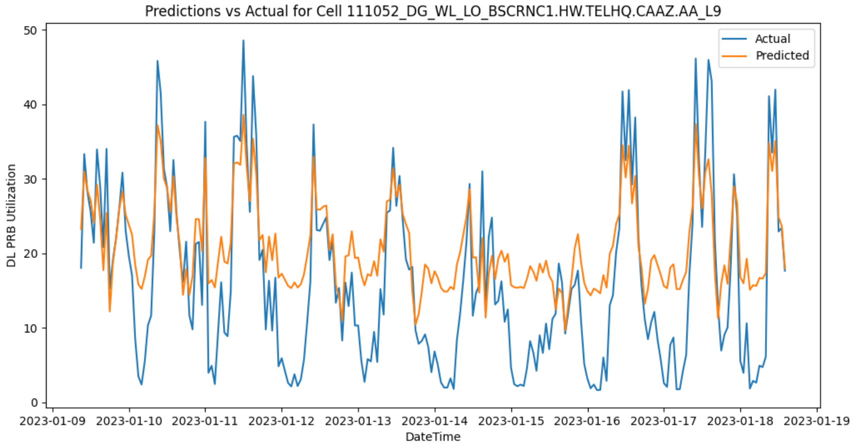


Figure 5.20: Cell 111052 L9 Actual Vs Predicted.

Evaluation for cell 111052 DG WL LO BSCRNC1.HW.TELHQ.CAAZ.AA L9:

MAE: 6.8241

R-squared: 0.5104

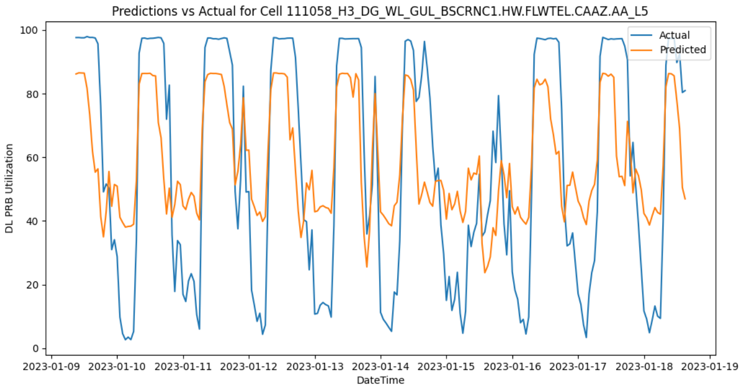


Figure 5.21: Cell 111058 L5 Actual Vs Predicted.

Evaluation for cell 111058 H3 DG WL GUL BSCRNC1.HW.FLWTEL.CAAZ.AA L5:

MAE: 21.1657

R-squared: 0.5533

LSTM Model Result Summary

In the above graphs presented for 10 randomly chosen cells, the LSTM model's performance in predicting Downlink PRB utilization can be summarized. The graphs show a similar trend for both actual and predicted values across most cells. This indicates that the LSTM model captures the general direction (increase or decrease) of PRB utilization over time. However, the key aspect to analyze is the difference between the actual and predicted values. Smaller gaps between the lines represent higher prediction accuracy. Some cells have larger and more frequent deviations between the lines especially for sudden spikes or dips. Compare the visual discrepancies between the Prophet model's graphs discussed earlier and the LSTM model's graphs. The cells where the Prophet model can better capture the magnitude of fluctuations in PRB utilization. The MAE values ranged from a minimum of around 6.2 to a maximum of around 21.7. Based on the provided MAE values for the Prophet model, it generally achieved lower errors compared to the LSTM model for most cells.

5.2.3 Prediction Result Using XGBoost model

The XGBoost model takes a different approach to predicting DL PRB utilization compared to Prophet and LSTM.The XGBoost model utilizes the XGBRegressor function within the xgboost library. Similar to Prophet and LSTM, the discussion of evaluation metrics used to assess XGBoost's performance is presented in this section. This include metrics like MAE and R-squared, providing insights into prediction. The following graphs compared visualization of actual and predicted PRB utilization from the XGBoost model.

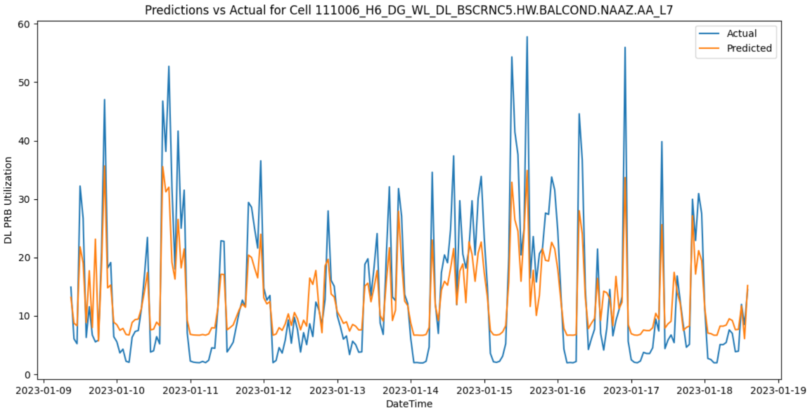


Figure 5.22: Cell 111006 L7 Actual Vs Predicted.

Evaluation for cell 111006 H6 DG WL DL BSCRNC5.HW.BALCOND.NAAZ.AA L7:

MAE: 4.8148

R-squared: 0.7296

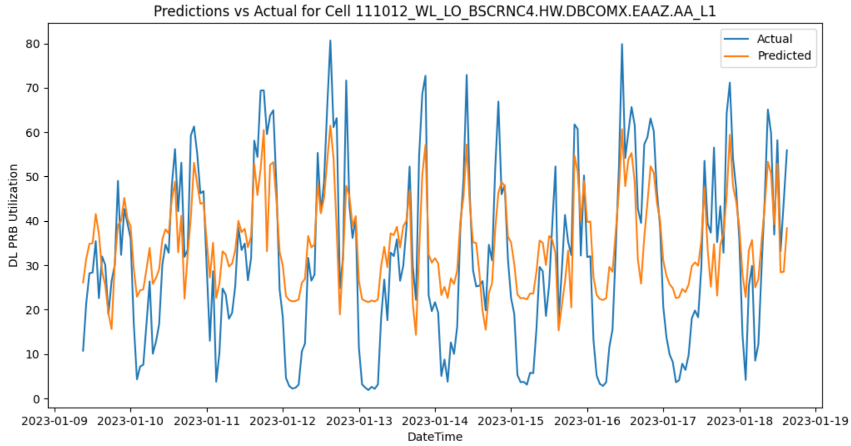


Figure 5.23: Cell 111012 L1 Actual Vs Predicted.

Evaluation for cell 111012 WL LO BSCRNC4.HW.DBCOMX.EAAZ.AA L1:

MAE: 10.5291

R-squared: 0.6216

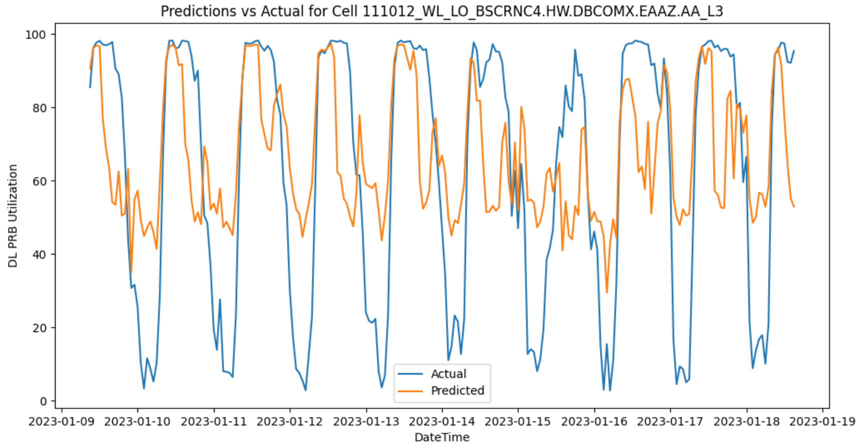


Figure 5.24: Cell 111012 L3 Actual Vs Predicted.

Evaluation for cell 111012 WL LO BSCRNC4.HW.DBCOMX.EAAZ.AA L3:

MAE: 22.8522

R-squared: 0.3760

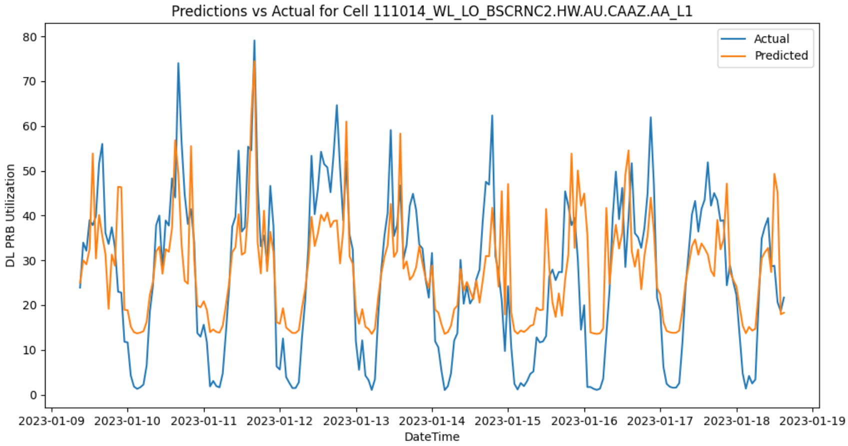


Figure 5.25: Cell 111014 L1 Actual Vs Predicted.

Evaluation for cell 111014 WL LO BSCRNC2.HW.AU.CAAZ.AA L1:

MAE: 9.7380

R-squared: 0.5664

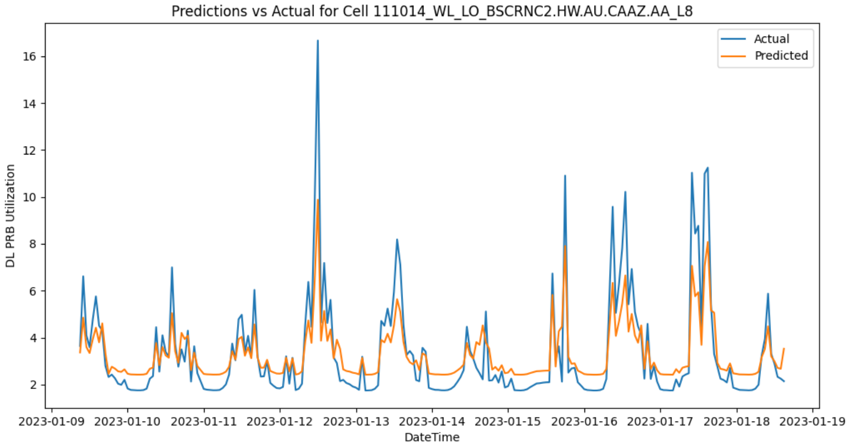


Figure 5.26: Cell 111014 L8 Actual Vs Predicted.

Evaluation for cell 111014 WL LO BSCRNC2.HW.AU.CAAZ.AA L8:

MAE: 0.7803

R-squared: 0.7400

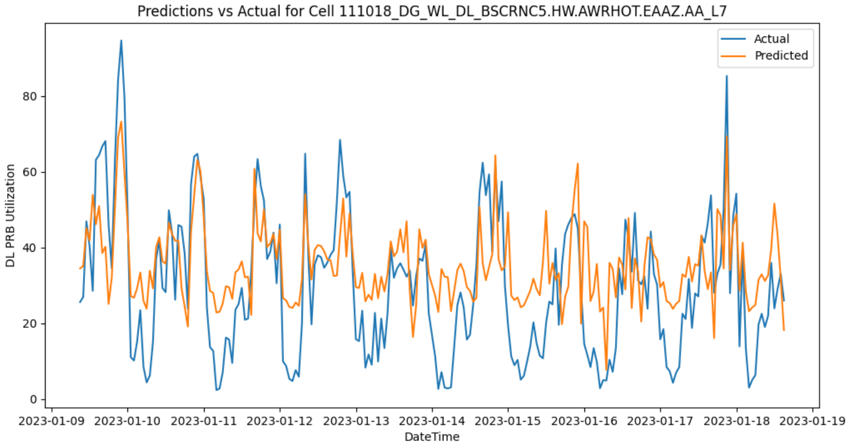


Figure 5.27: Cell 111018 L7 Actual Vs Predicted.

Evaluation for cell 111018 DG WL DL BSCRNC5.HW.AWRHOT.EAAZ.AA L7:

MAE: 12.3891

R-squared: 0.4012

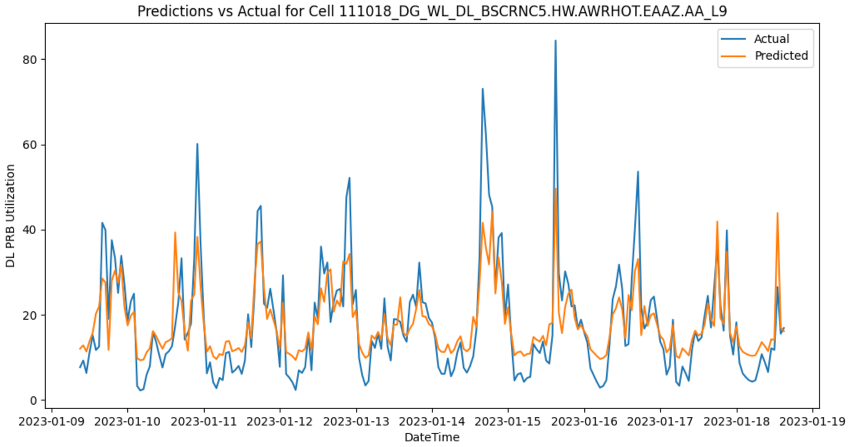


Figure 5.28: Cell 111018 L9 Actual Vs Predicted.

Evaluation for cell 111018 DG WL DL BSCRNC5.HW.AWRHOT.EAAZ.AA L9:

MAE: 5.0718

R-squared: 0.7139

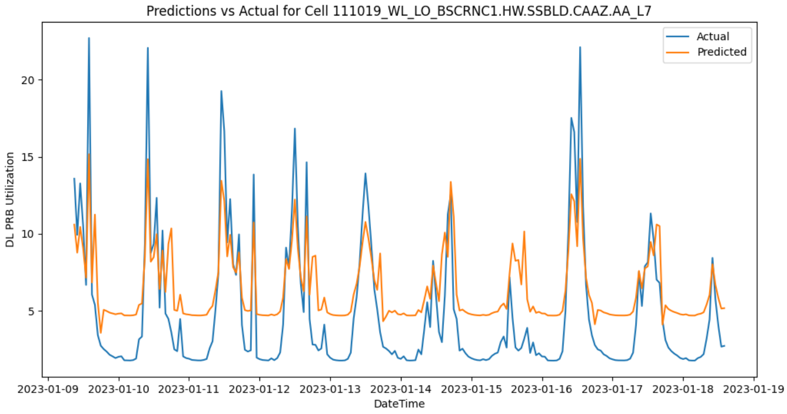


Figure 5.29: Cell 111019 L7 Actual Vs Predicted.

Evaluation for cell 111019 WL LO BSCRNC1.HW.SSBLD.CAAZ.AA L7:

MAE: 2.5516

R-squared: 0.5374

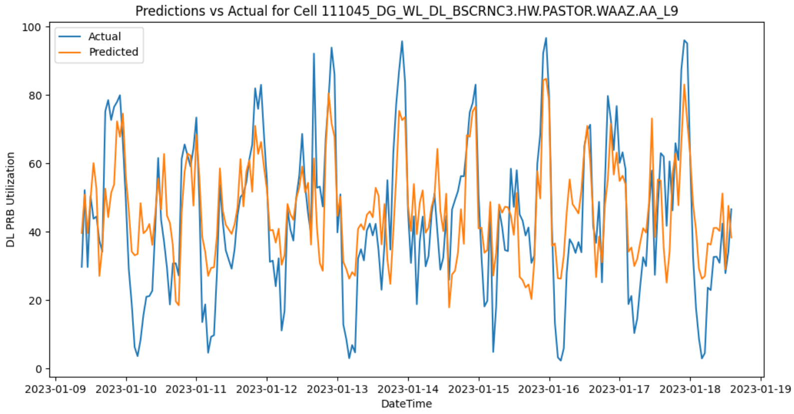


Figure 5.30: Cell 111045 L9 Actual Vs Predicted.

Evaluation for cell 111045 DG WL DL BSCRNC3.HW.PASTOR.WAAZ.AA L9:

MAE: 12.0458

R-squared: 0.5922

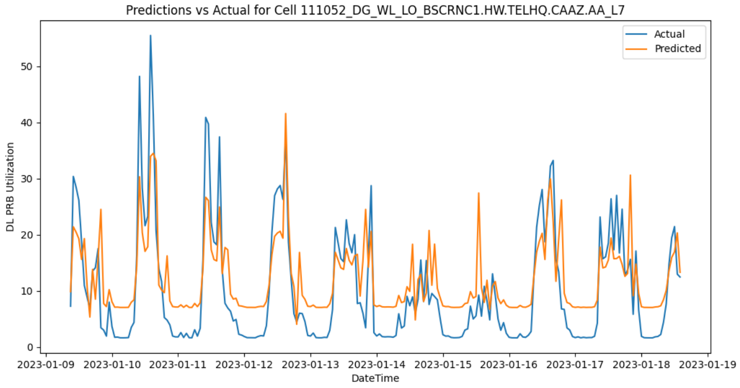


Figure 5.31: Cell 111052 L7 Actual Vs Predicted.

Evaluation for cell 111052 DG WL LO BSCRNC1.HW.TELHQ.CAAZ.AA L7:

MAE: 5.2390

R-squared: 0.6122

XG-Boost Model Result Summary

The provided results showcase a range of MAE values across different cells, from a minimum of 0.78 to a maximum of 22.85. The R-squared values in the results exhibit variation, with some cells which is ranging from 0.74 to 0.38. the graphs show a similar trend for both actual and predicted values across most cells. This shows that the XGBoost model captures the general direction of PRB utilization over time but the gaps between the actual and predicted values, especially for sudden dips or spikes are different for some cells as LSTM model. Based on the results, XGBoost and LSTM models seem to exhibit competitive performance in terms of both MAE and R-squared values. This suggests that both approaches can achieve similar levels of accuracy for predicting PRB utilization in this dataset. The XGBoost model demonstrates the ability to capture the general trends in PRB utilization for most cells, with some achieving high prediction accuracy.

Overall Evaluation for the Three Models

Table 5.1: Overall Evaluation

Model Name	R-Square	MAE
Prophet	0.9514	4.9838
LSTM	0.6310	17.6032
XGBoost	0.6024	17.4155

5.3 Sort and Prioritizing Algorithm

This algorithm tackles the task of prioritizing cellular network cells based on how much of their PRBs are predicted to be in use. It takes a DataFrame containing information about each cell, including predicted PRB utilization, date-time, eNodeB ID (identifier for the base station), and Band (frequency layer).

It prioritizes cells by iterating through unique combinations of hour, eNodeB ID, and Band. For each combination, it filters the data to include only entries for that specific time, base station, and frequency band. Then sorts these cells by their predicted PRB utilization, with the most utilized cells at the top. It can identify overloaded cells which have high PRB usage.

Next, It separates overloaded cells from those with lower utilization (remaining cells). It stores this prioritized information for each unique hour, eNodeB ID, and Band combination. This stored information has entries for Overloaded and Remaining cells, each containing a list of cell names and their corresponding predicted PRB utilization. Finally, It identifying the prioritized data.

Table 5.2: Sample Result for Sort and Prioritizing Algorithm.

Date	**Hour**	**eNodeB ID**	**Band**	**Overloaded Cell**	**Remaining Cell**
1/10/2023	21:00	111583	L1800	111583_L1:95.84 111583_L3:92.85	111583_L2:78.3
1/10/2023	21:00	111583	L2600	111583_L4:91.5	111583_L6:83.01 111583_L5:65.25
1/10/2023	21:00	111583	L800	111583_L7:98.29	111583_L9:75.64 111583_L8:37.16
1/10/2023	21:00	111584	L1800	111584_L2: 99.38, 111584_L3:95.42	111584_L1:88.45
1/10/2023	21:00	111584	L2600	111584_L6:91.58	111584_L5: 87.84 111584_L4:67.78
1/10/2023	21:00	111584	L800	111584_L7:95.22 111584_L9: 95.21 111584_L8:93.61	
1/10/2023	21:00	111585	L1800	111585_L1: 95.25, 111585_L3:91.06	111585_L2:55.5
1/10/2023	21:00	111585	L2600		111585_L4:86.09 111585_L6: 73.87 111585_L5:49.08
1/10/2023	21:00	111585	L800	111585_L7:94.36	111585_L8: 72.38, 111585_L9:58.77
1/10/2023	22:00	111583	L1800	111583_L1:95.79	111583_L3: 88.77 111583_L2:64.86
1/10/2023	22:00	111583	L2600	111583_L4:90.26	111583_L6: 80.79, 111583_L5:52.75
1/10/2023	22:00	111583	L800	111583_L7:99.36	111583_L9: 79.14, 111583_L8:31.14
1/10/2023	22:00	111583	L1800	111584_L2: 97.46, 111584_L3:96.79	111584_L1:87.36
1/10/2023	22:00	111584	L2600		111584_L6: 88.25, 111584_L5: 83.32, 111584_L4:77.61
1/10/2023	22:00	111584	L800	111584_L7:96.85, 111584_L9: 96.30, 111584_L8:93.79	
1/10/2023	22:00	111585	L1800	111585_L1:91.92	111585_L3: 89.86, 111585_L2:50.52
1/10/2023	22:00	111585	L2600		111585_L4:84.91, 111585_L6: 73.91, 111585_L5:39.7
1/10/2023	22:00	111585	L800	111585_L7:92.07	111585_L9: 66.98, 111585_L8: 62.68

Chapter 6: **Conclusion and Future Work**

6.1 Conclusion

The main contribution of this thesis is the application of machine learning techniques to balance the loads between the frequency layers based on the future predicted resource utilization rate. In this work three machine learning models are tested for prediction of PRB utilization per cell for every hours of the day in growing network load conditions. Out of three tested machine learning models, Prophet provided the best results and was selected as the best machine learning model for our data set. The previous results showed that the best model Prophet achieved R=Square of 0.9514 and MAE of 4.9838. LSTM and XGBoost obtained R-squared values of approximately 0.63 with respective MAE values of around 17.

This result indicating Prophet has better performance for this data. However, LSTM and XGBoost are not optimal since it yielded higher MAE and lower R=Square value than Prophet. Sorting and prioritization algorithm developed to identify overloaded cells based on the predicted PRB utilization. This work lays the groundwork for implementing intelligent load balancing strategies in LTE networks.

6.2 Future Work

This research opens doors for exciting future exploration. One potential avenue could involve developing a load balancing framework that leverages Prophet-based PRB utilization predictions. This framework could dynamically adjust resource allocation across frequency layers, optimizing network performance and user experience. Additionally, exploring the applicability of Prophet for predicting other network parameters relevant to load balancing and resource optimization could further enhance network management capabilities.

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