## ABSTRACT

This paper presents a comprehensive approach to network slicing and resource allocation in 5G networks using machine learning techniques. Firstly, a hybrid model combining Bidirectional Long Short-Term Memory (Bi-LSTM) and Long Short-Term Memory (LSTM) neural networks is proposed for efficient resource allocation and slice selection.

The model demonstrates promising results in accurately classifying network slices based on various features, achieving high accuracy levels after training and evaluation.

Furthermore, a simulated network slicing controller is developed to allocate resources based on requested slices, providing insights into the allocation process. Additionally, an Online Gradient Descent (OGD) algorithm is employed to optimize resource allocation in real-time, iteratively adjusting allocation based on observed errors between predicted and actual bandwidth allocations.

The OGD-based optimization significantly improves resource utilization, as demonstrated through comparison with non-optimized allocations. The proposed methodology offers a promising framework for enhancing network slicing efficiency and resource utilization in 5G networks.

## ACKNOWLEDGEMENT

I would like to express my sincere gratitude to my professor, ***MRS RASHMI GUPTA***, for her invaluable guidance and unwavering support throughout my project. Her expertise and patience have been instrumental in shaping my understanding and skills in the field of deep learning in telecommunications.

I gained expertise in deep learning methods, including how to use and train LSTM (Long Short-Term Memory) and Bi-LSTM neural networks. In order to optimise network slicing in 5G, I also gained expertise in data pretreatment, model evaluation, and the use of deep learning. I developed my skills in data gathering, data analysis, and result interpretation. This encompasses the crucial data-driven research processes of feature engineering, model calibration, and data preprocessing. I gained knowledge on how to spot and solve problems related to 5G network slicing. I came up with creative ideas and approaches to boost resource allocation and network performance.

My project probably requires a synthesis of expertise that extend 5G networks, deep learning, and telecommunications engineering. This interdisciplinary approach is helpful in tackling problems in the actual world. This project has been an enriching experience, allowing me to gain a deeper understanding of the technologies that shape our connected world.

I would also like to extend my thanks to my fellow students and colleagues who provided assistance during data collection and analysis. Their collaborative spirit was instrumental in the project's completion.

I am also thankful for the resources and facilities provided by our institution, which greatly contributed to the success of this endeavour.



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## I. INTRODUCTION

The advent of 5G networks heralds a new era of unprecedented connectivity, promising not only faster internet speeds but also a transformative impact on industries such as healthcare, manufacturing, and autonomous transportation. However, this transformative potential is accompanied by a unique set of challenges. One of the foremost challenges in 5G network management is the efficient allocation of resources to cater to the diverse demands of a multitude of services and applications.

## II. PROBLEM STATEMENT

The research addresses the challenges in Quality of Service (QoS) optimization for 5G networks, focusing on network slicing and resource allocation. The key problems addressed by the project include:

- Inefficient Resource Allocation: Current 5G networks face inefficiencies in resource allocation, leading to suboptimal utilization of bandwidth resources.
- Dynamic Network Slicing: The need for dynamic and efficient network slicing to cater to diverse user requirements, such as different use cases, LTE/5G categories, technologies supported, and varying time and days.
- Enhancing QoS with Deep Learning: Leveraging deep learning techniques, specifically Bidirectional Long Short-Term Memory (Bi-LSTM) and Long Short-Term Memory (LSTM) models, to improve QoS by capturing both short-term and long-term dependencies in the data.
- Integration of Statistical Information: Incorporating statistical information regarding network slices to enhance decision-making processes in resource allocation.

## III. RESEARCH OBJECTIVE

The primary objective is to develop a hybrid deep learning model that combines Bi-LSTM and LSTM architectures to address the challenges mentioned above.

The model aims to dynamically allocate resources based on the unique requirements of network slices, thereby improving QoS in 5G networks.

The proposed solution will be evaluated using real-world datasets, demonstrating its effectiveness in optimizing resource allocation and enhancing overall network performance.

## IV. SIGNIFICANCE OF THE STUDY

This research holds significant implications for the telecommunications industry, as it seeks to address a critical issue in the deployment of 5G networks. By leveraging deep learning techniques, we endeavour to provide a more adaptive and intelligent network slicing solution, which can improve the efficiency, reliability, and scalability of 5G networks. Moreover, the outcomes of this study contribute to the broader field of deep learning applications in network management.

In the following sections, we will delve into the methodology employed, present our findings, and discuss their implications. By the end of this research, we aim to provide valuable insights and recommendations that can empower network operators and service providers in realizing the full potential of 5G networks through effective network slicing.

V. LITERATURE SURVEY

| S.No. | Technique | Description |
|---|---|---|
| 1. | 5G network slicing using SDN AND NFV<br>(published on: 17 November 2019) Parameters and components being discussed in this research work are:<br>• 5G Service Quality and Business Requirements<br>• Softwarization and Slicing Paradigms<br>• Technology Enablers: The article provides a tutorial on technology enablers for 5G network slicing, which includes SDN, NFV, Multi-Access Edge Computing (MEC), cloud/fog computing, network hypervisors, virtual machines, and containers.<br>• Industrial Initiatives and Projects that promotes the adoption of SDN and NFV for accelerating 5G network slicing are surveyed. | Alcardo Alex Barakabitze et al[1]., they start by discussing 5G service quality and business requirements, followed by an exploration of 5G network softwarization and slicing, which covers key concepts, historical context, and diverse use cases. Additionally, we provide insights into 5G network slicing technology enablers, including SDN, NFV, MEC, cloud/Fog computing, network hypervisors, Virtual Machines, and containers. We also delve into significant industrial initiatives and projects aimed at accelerating 5G network slicing through SDN and NFV adoption |

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| | • Architectural Approaches: The article compares different 5G architectural approaches in terms of practical implementations, technology adoptions, and deployment strategies.<br>• Open-Source Orchestrators<br>• Standardization Efforts<br>• Management and Orchestration<br>• Future Challenges and Research Directions | |
| 2. | NFV and SDN based slicing model (Published on 24 April 2017) Parameters and components being discussed in this research work are:<br>• The article focuses on satisfying users' different QoS requirements in 5G networks.<br>• Network Slicing<br>• Resource Allocation Schemes<br>• Mobility Management Schemes<br>• Logical Architecture<br>• Power and Subchannel Allocation<br>• Simulation Results<br>• Open Issues and Challenges | Haijun Zhang et[2] al., they have presented a logical architecture for network slicing based 5G systems, and discussed the evolution of<br>network architecture based on SDN and NFV technologies, as well as the implementation of network slicing. Further they have considered<br>various network slicing scenarios and introduced a resource allocation mechanism tailored for Qos requirements and interference<br>constraints of uRLLC, eMBB and IoT service slices. |
| 3. | A Hybrid Deep Learning model (LSTM-CNN).<br>(Published on 27 January 2022,<br>Journal of network and systems management)<br>Parameters and components being discussed in this research work are:<br>• Next-Generation Networks | Sulaiman Khan[3] et al., a hybrid machine learning based model is proposed in this research work to ensure accurate allocation of network slice based on the incoming new traffic requests, optimum utilization of |

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| | • Reconfigurable Wireless Network Slicing: Reconfigurable wireless network slicing is identified as a key element for 5G and 6G networks.<br>It enables operators to run multiple network instances using a single infrastructure to provide better Quality of Service (QoS).<br>• Artificial Intelligence and Machine Learning<br>• Hybrid Deep Learning Model<br>• Validation and Applicability | network resources, load balancing, fault detection, and assignment of master slice in case of slice failure or slice over-flow conditions. |
| 4. | Resource Allocation Method Based on GCN-LSTM in 5G Network.<br>(Published on 3 March 2023, IEE Communications Letters)<br>Parameters and components being discussed in this research work are:<br>• Resource Allocation in 5G<br>Networks<br>• Allocation Algorithm<br>• Historical 5G Traffic Data: The<br>algorithm utilizes historical 5G<br>traffic data, which is divided into three time periods. These time periods help capture different aspects of the data, allowing for a more comprehensive analysis.<br>• Combining Spatial and Temporal Features<br>• Resource Allocation Strategy<br>• Simulation Results | Resource Allocation Method Based on GCNLSTM in 5G Network Xu Gao[4] et al., have proposed algorithm based on GCNLSTM((Graph Convolution Network - Long Short-Term Memory). The historical 5G traffic data is divided into three time periods, and the spatial features of each period can be obtained through GCN. LSTM model is used to extract the temporal features. The combination of spatial and temporal features can achieve a high-precision prediction of 5G traffic data. Eventually, the 5G traffic prediction results of GCN-LSTM are used as<br>the strategy basis for resource allocation. |
| 5. | OFDMA communication system (published in 2017, IEEE)<br>Parameters and components being discussed in this research work are:<br>• 5G Mobile Network Flexibility<br>• Network Slicing | Sunday O. Oladejo et al[5]., they have investigated the resource allocation problem of achieving maximum capacity with the transmit power, allocated bandwidth as part of the |

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| | • Resource Allocation Challenge<br>• Simulation Focus: This research focuses on the resource allocation problem with specific constraints, including transmit power and allocated bandwidth, in a sliced multi tenant network. The objective is to achieve maximum network capacity.<br>• Simulation results | constraints in a sliced multi-tenant network. Through their simulations, they have demonstrated how the number of users in a slice affects the capacity of an MVNO and second how the transmit power improves the capacity of the MVNO and how the number of slices affects the capacity |
| 6. | Resource allocation method using deep learning. (Published in 5 December 2018, Springer Nature) Parameters and components being discussed in this research work are:<br>• Wireless Personal Communication: The article focuses on wireless personal communication, emphasizing its popularity and the demands for high transmission speed and Quality of Service (QoS) in the context of 5G communication systems.<br>• Resource Allocation<br>• Convolutional Neural Network (CNN): this research uses CNN to process and analyze the channel information efficiently.<br>• Utilizing Small-Scale Channel Information: Deep learning is employed to fully utilize small scale channel information, especially in situations where the channel environment is changing rapidly. This approach is presented as an alternative to traditional resource optimization methods.<br>• Simulation results: The article presents simulation results that demonstrate the performance of the proposed resource allocation method. It is shown to be comparable to the Minimum Mean Square Error (MMSE) method and superior to the Zero Forcing (ZF) method. Additionally, the proposed method is noted for its reduced computational time compared to traditional methods. | Dan Huang et al[6]., have developed a novel resource allocation method using deep learning to squeeze the benefits of resource utilization. By generating the convolutional neural network using channel information, resource allocation is to be optimized. The deep learning method could help make full use of the small-scale channel information instead of traditional resource optimization, especially when the channel environment is changing fast. |

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| 7. | Comprehensive survey of 5g network slicing (published in June 2019, IEEE Wireless Communication) Parameters and components being discussed in this research work are:<br>• New Use Cases and Diverse Requirements: The paper highlights the new use cases from vertical industries in 5G and how these scenarios bring diverse and challenging requirements. These requirements include a broader range of performance, cost considerations, security protection, and mobility management.<br>• Customized Logical Networks: It introduces the concept of slicing a single physical network into several logical networks customized to meet different unique requirements. This approach is seen as a promising way to address the divergent requirements of 5G applications.<br>• Key Enabling Technologies<br>• 3GPP Standardization and Industry Implementation<br>• Open Issues and Challenges: | Shunliang Zhang[7] have he is providing a comprehensive survey of 5G network slicing. He has also covered related key enabling technologies, including network function virtualization and modularization, dynamic service chaining, management and orchestration are discussed. |
| 8. | Have proposed a three-layer network slicing framework for 5G (published in 2017, IEEE Communication Magazine) Parameters and components being discussed in this research work are:<br>• 5G Networks<br>• Multi-Service Network<br>• Network Slicing<br>• Survey: The article's primary purpose is to act as a survey or review of the topic of 5G network slicing.<br>• State of the Art: Xenofon Foukas et al., review the current state of the art in 5G network slicing, summarizing existing research and developments.<br>• Framework: The authors present a framework for discussing and categorizing the existing work related to 5G network slicing in a comprehensive manner.<br>• Maturity Evaluation: Using their framework, Xenofon Foukas et al., assess the maturity of current proposals and solutions in the field of 5G network slicing.<br>• Open Research Questions | Xenofon Foukas et al., have proposed a framework that supports flexible deployment and management of diverse network applications over one common infrastructure. The framework contains a 5G software defined infrastructure (5G-SDI) layer, virtual resource layer, application and service layer, and a slicing management and orchestration (MANO) functional component. They have also discussed remaining challenges and future research directions. |

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| 9. | Virtual networking mechanism (published in 18 June 2020, Journal of Network and Systems Management) Parameters and components being discussed in this research work are:<br>• 5G networks<br>• Network Resilience: The primary concern is the resilience of the 5G network. This refers to the network's ability to maintain services and recover quickly from network failures.<br>• Network Virtualization<br>• gNBs (Macrosites): The architecture utilizes gNBs (macrosites) as part of the network infrastructure. These are likely base stations or key network nodes.<br>• Self-Organizing Ad Hoc Network<br>• Optimization Formulation<br>• Heuristic: A heuristic method is proposed for network survivability.<br>• Simulations<br>• Auxiliary Capacity: The trade off between a provider's own network and auxiliary capacity from another provider is explored. This means considering the use of external resources when needed for resilience.<br>• Priority for Traffic Groups: The study also investigates how to provide priority for certain traffic groups to ensure service survivability. | Rohit Abhishek et al[9]., illustrates network virtualizations with a variety of different providers, which call for network slicing in fifth generation networks. |
| 10. | MILP(mixed-integer linear programming) optimization model (published in May 2020, IEEE transaction on mobile computing) Parameters and components being discussed in this research work are:<br>• Network Slicing (NS)<br>• Network Function Virtualization (NFV)<br>• Software Defined Networking (SDN)<br>• Service Function Chains (SFC): SFCs are mentioned as part of the network slicing approach. They consist of a sequence of network functions that handle specific traffic within a slice.<br>• MILP Optimization Model | Rami Akrem Addad[10] et al., they introduce a novel architecture for Network Slicing (NS) in 5G and beyond systems, addressing the complexities of deploying Network Functions (NFs) across different domains. It presents a MILP optimization model for cost-effective resource allocation and a greedy-based heuristic to balance runtime and network slice deployment. |

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| | • Cost-Optimal Deployment<br>• Greedy-Based Heuristic: In addition to the optimization model, the article introduces a greedy-based heuristic. This heuristic explores trade-offs between execution runtime and network slice deployment.<br>• Required Delay and Bandwidth:<br>• Virtualized Network Functions (VNF) and Physical Nodes: The solution efficiently manages the utilization of both virtualized network functions and physical network nodes.<br>• Reducing Operating Expenditure (OPEX): The proposed approach is designed to reduce the service provider's operating expenditure, making network operations more cost effective. | The solution ensures required quality parameters and efficient resource utilization, reducing operating costs for service providers. |
| 11. | A Survey on Resource Allocation for 5G Heterogeneous Networks Published in 2021, IEE Communication Surveys and Tutorials) Parameters and components being discussed in this research work are:<br>• Various service requirements<br>• Heterogeneous Networks (HetNets)<br>• Resource Allocation (RA) Algorithms<br>• RA(resource allocation) Models<br>• RA Classification<br>• Different network scenarios of HetNets are introduced.<br>• Challenging issues<br>• Potential Structures for 6G Communications | [11] Yongjun Xu et al., explores Heterogeneous Networks (HetNets) within the context of 5G mobile communication. HetNets, an evolution of network structures, enhance spatial resource reuse and improve user quality of service by integrating small cells with macrocells. Given mutual interference and limited spectrum resources in HetNets, efficient Resource Allocation (RA) algorithms are crucial for reducing interference and enabling spectrum sharing. The article introduces HetNets, discusses RA models, categorizes current RA algorithms, and outlines future research trends |

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| 12. | LSTM-A2C(Long Short-Term Memory Advantage Actor-Critic) model (published on 9th September 2020) Parameters and components being discussed in this research work are:<br>• Network slicing<br>• Demand-Aware Inter-Slice Resource Management: Efficient resource allocation across different network slices is a key focus. This research work discusses resource management that is aware of the varying demands of different services.<br>• Scenario: The scenario involves a radio access network with several network slices. In this scenario, base stations share the same physical resources, such as bandwidth or slots.<br>• Advantage Actor-Critic (A2C)<br>• User Mobility<br>• Long Short-Term Memory (LSTM)<br>• LSTM-A2C Algorithm<br>• Performance Verification | [12] Rongpeng Li et al., focuses on network slicing for efficient provisioning of diverse services over the same infrastructure. It addresses demand-aware inter-slice resource management in a multi-slice radio access network. The approach combines deep reinforcement learning (DRL), specifically the LSTM-A2C algorithm, to handle varying service demands and user mobility. Extensive simulations validate the LSTM-A2C algorithm's performance. |
| 13. | Provisioning and Architecture Models for 5G Network Slicing (published in 2018,IEEE Wireless Communication and Networking Conference [WCNC]) Parameters and components being discussed in this research work are:<br>• 5G Mobile Networks<br>• Network Slicing<br>• Network Slice Isolation<br>• Mobile Network Operator (MNO): MNOs are responsible for creating network slices. These slices can then be rented out to third-party organizations like enterprises.<br>• Provisioning Models: The article introduces different novel provisioning models for third-party network slices. These models are designed to ensure isolation and address the needs of various applications and verticals. | [13] Peter Schneider et al., explores 5G network slicing for specific services and applications. They discuss the need for isolation within network slices, especially for sensitive services. The paper mentions that it introduces different novel provisioning models for 3rd-party network slices and discusses their isolation properties. It also introduces new network architecture deployment models that include 3rd-party owned network infrastructure. |

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| | • Isolation Properties: The isolation properties of the provisioning models are discussed in the article. Achieving the highest level of isolation is a key consideration, particularly for sensitive applications.<br>• Common Infrastructure: The article suggests that network slices relying solely on common infrastructure may not meet the highest isolation requirements.<br>• New Network Architecture: To address the isolation and security needs of third-party network slices, this research work proposes new network architecture deployment models. These models include 3rd-party-owned network infrastructure.<br>• Highly Secure Mobile Communication Services: this research work discusses how the proposed network architecture deployment models can be used by third parties to implement highly secure mobile communication services. | |
| 14. | The concept and framework of network slicing for 5G. (Published in 2017, IEEE Computer Society) Parameters and components being discussed in this research work are:<br>• This research work does not contain specific parameters or technical details.<br>• It gives a high-level overview of the concept of "network slicing" in 5G networks, its benefits, challenges, and the intention of the research.<br>• It discusses the background of network slicing, its advantages, and outlines future research directions.<br>• This research work is more focused on the concept and challenges rather than specific technical parameters. | [14] This research work discusses the concept of network slicing in 5G, which offers a Network as a Service (NaaS) for various use cases. It enables network operators to create multiple virtual networks on a shared infrastructure, providing flexibility for deploying services tailored to specific requirements. The article presents the background of network slicing, introduces a framework, and addresses the challenges and future research directions related to this emerging technology. The specific technology or model used is not mentioned, as the focus is on the concept and its implications. |

Table 1: literature survey

From Table 1 it can be concluded that a lot of work has been reported for network frame allocation, slice fragmentation, DDoS attacks identification, ensuring security by applying virtualization techniques or other neural network-based models, but there is no significant work reported for automatic slice allocation in 5G/6G networks. This research distinguishes itself by offering :

- Hybrid Bi-LSTM and LSTM architecture:
  This project stands out by adopting hybrid approach, combining both bidirectional long short-term memory (Bi-LSTM) and long short-term memory (LSTM) models. This hybrid architecture capture both short-term and long-term dependencies, providing a more comprehensive understanding of network behavior.

  **Bi-LSTM (Bidirectional LSTM):**

  - ⇔ Advantage: Bi-LSTM is effective in capturing dependencies in both forward and backward directions in sequential data, allowing it to capture contextual information effectively.
  - ⇔ Purpose: It's used for better resource allocation and slice selection, where bidirectional information flow can capture dependencies from both past and future sequences.
  - ⇔ Bi-LSTM processes the input sequence in both forward and backward directions, capturing information from past and future states. This bidirectional context helps in understanding the dependencies in both directions.
  - ⇔ It is beneficial when the information from both earlier and later parts of the sequence is crucial for making predictions.
  - ⇔ In network slicing, bidirectional context may be relevant for understanding the historical and future patterns of resource utilization.

- **LSTM (Long Short-Term Memory):**
  - ⇔ Advantage: LSTM is designed to handle long-term dependencies in sequential data by addressing the vanishing gradient problem.
  - ⇔ Purpose: Used for capturing statistical information regarding network slices, particularly focusing on long-term dependencies in the data.
  - ⇔ LSTM is known for handling long-term dependencies in sequential data. It is effective in capturing relationships that span a larger number of time steps.
  - ⇔ In the context of network slicing, where the requirements and conditions may evolve over time, LSTM helps in learning patterns that extend beyond short-term fluctuations.

- **Why both?**

Bi-LSTM Advantages:

- Capturing Bidirectional Dependencies: Bi-LSTM is capable of capturing dependencies in both forward and backward directions, which can be beneficial in tasks where understanding context from both past and future is important.
- Enhanced Memory: Bidirectional processing helps in capturing long-term dependencies and relationships in sequential data.

LSTM Advantages:

- Sequential Learning: LSTM is effective in learning and remembering sequential patterns, making it suitable for tasks where the order of data is crucial.
- Memory Cell Control: LSTM has a memory cell that can store and retrieve information over long sequences, allowing it to capture long-term dependencies.

Hybrid Model Considerations:

- Complementary Strengths: Combining LSTM and Bi-LSTM may offer complementary strengths. LSTM can focus on sequential patterns, while Bi-LSTM captures bidirectional dependencies.
- Task Complexity: For certain tasks, especially those involving complex patterns and dependencies, a hybrid model might outperform a single architecture.

What is network slicing?

Network slicing is like having separate, customized highways for different types of vehicles. In my dataset, the "slice Type" column represents different types of network slices, such as eMBB (Enhanced Mobile Broadband), mMTC (Massive Machine-Type Communication), and URLLC (Ultra-Reliable Low-Latency Communication). Each of these slices is tailored to meet specific needs like high data rates, massive device connectivity, or ultra-reliable low-latency communication.

For example:

→ "eMBB" slice could be like a fast lane on the highway, prioritizing high-speed data for smartphones.

→ "mMTC" slice could be a lane dedicated to IoT devices, ensuring massive connectivity with a guaranteed bitrate (GBR).

→ "URLLC" slice could be a lane reserved for critical applications in Industry 4.0, offering ultra-reliable and low-latency communication.

Resource Allocation:

Now, let's think of resources as the lanes on these highways and how efficiently they are used for each type of vehicle.

In my dataset:

- → "GBR" in the "slice Type" column indicates Guaranteed Bit Rate, suggesting a specific bandwidth is allocated for communication in that slice.
- → "Packet Loss Rate" and "Packet delay" are measures of the quality of service, indicating how well the allocated resources are utilized. For example, "Non-GBR" slices may not guarantee a fixed bitrate but could have lower requirements for reliability and latency.

For example:

- → In the "mMTC" slice, where IoT devices are communicating, a certain amount of bandwidth is guaranteed (GBR), ensuring reliable and consistent connectivity with minimal packet loss and delay.
- → In the "eMBB" slice for smartphones, while there might not be a guaranteed bitrate, the emphasis might be on providing high data rates during peak hours.

VI. ATTRIBUTES USED FOR HYBRID MODEL:

- **Use case: these includes:**

- Smartphones

- AR/VR/Gaming

- IOT devices

- Industry 4.0

- Healthcare

- Smart city and home

- Public safety

- Smart transportation

- LTE/5G category: It represents different scenarios in LTE and 5G network environments. The "LTE/5g Category" attribute helps categorize these scenarios based on specific aspects or characteristics of the networks.

EG: Suppose you have the following "LTE/5g Category" values:

1: Urban Area

2: Rural Area

3: Indoor Venue

4: Outdoor Venue

5: Public Transportation

- **Technology Supported:**

This attribute indicates the technology that the network supports. It specifies whether the network is based on LTE, 5G, or both, and might further specify the subtypes of 5G technology (e.g., IoT-specific variations).

- **Day:**

This attribute represents the day on which the network conditions and usage are being considered. It helps capture the variations in network conditions and traffic patterns across different days.

- **Time:**

This attribute indicates the specific time slot during the day when the network conditions and usage are being considered. Similar to the "Day" attribute, it captures the variations in network conditions throughout the day.

- **GBR (Guaranteed Bit Rate):**

This attribute indicates whether the network slice has guaranteed bit rate characteristics. GBR specifies that the network slice must provide a minimum and guaranteed data rate to the associated services.

- **Packet Loss Rate:**

This attribute represents the rate at which data packets are lost or dropped during transmission. It is a crucial quality metric for network performance.

- **Packet Delay:**

This attribute indicates the delay or latency experienced by data packets as they travel through the network. It is another important quality metric that impacts user experience.

- **Slice Type:**

This attribute specifies the type of network slice that is being considered for the given scenario. The possible slice types could include "eMBB" (enhanced Mobile Broadband), "URLLC" (Ultra-Reliable Low Latency Communication), and "mMTC" (massive Machine Type Communication). Each type corresponds to different QoS requirements and service characteristics.

## VII. ATTRIBUTES USED FOR RESOURCE ALLOCATION

Timestamp: The date and time when the measurement was taken.

User_ID: An identifier for each user.

Application_Type: The type of application or service being used by the user.

Signal_Strength: The signal strength in decibels (dBm).

Latency: The latency or delay in milliseconds (ms).

Required_Bandwidth: The amount of bandwidth required for the application in Megabits per second (Mbps) or Kilobits per second (Kbps).

Allocated_Bandwidth: The actual bandwidth allocated by the system, also in Mbps or Kbps.

Resource_Allocation: The percentage of allocated bandwidth compared to the required bandwidth.

## VIII. ARCHITECTURE OF THE MODEL:

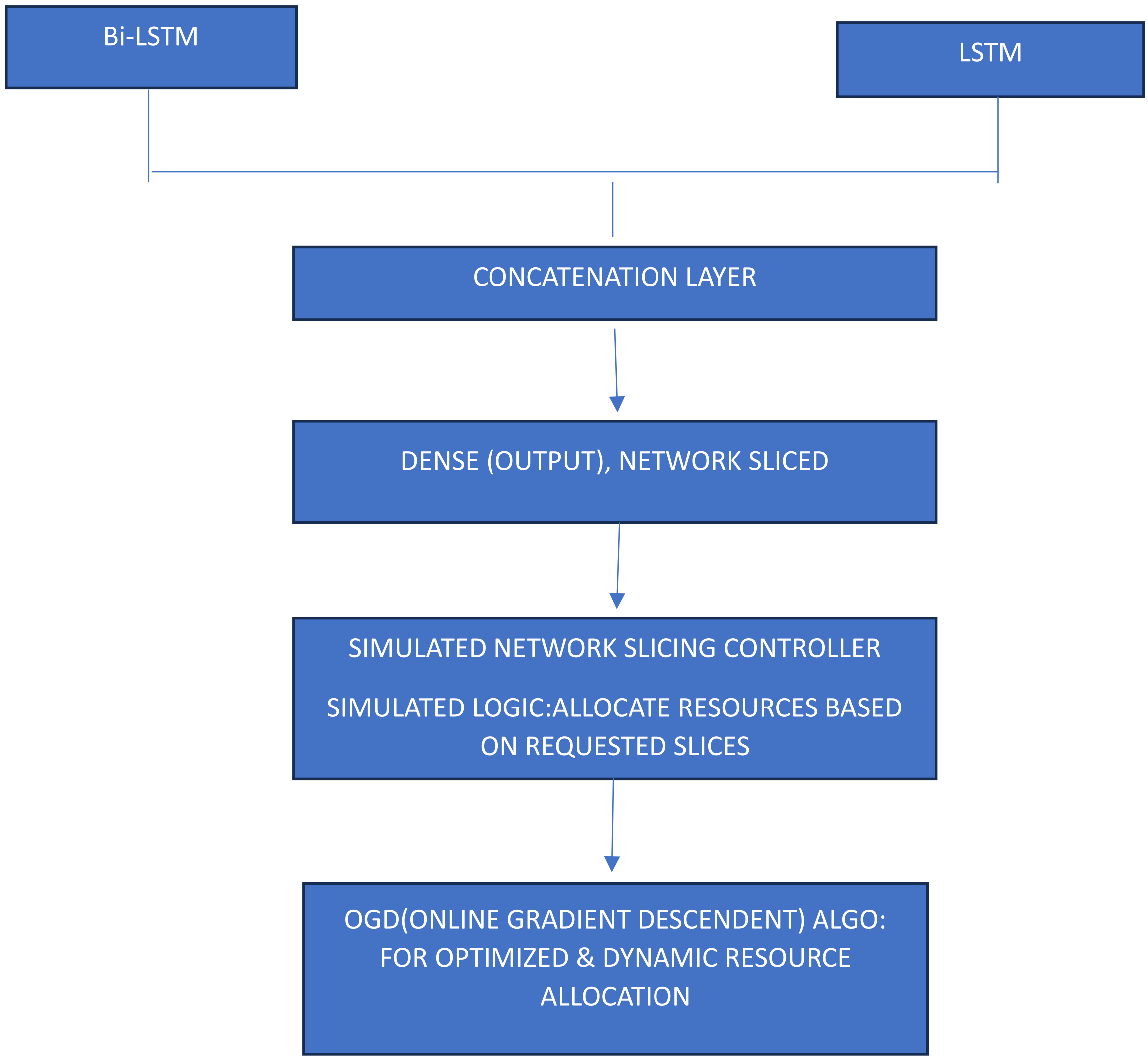


Fig 1: architecture of the model

1. Input Layer:

The input layer (X_train) represents the features of your dataset. It's a sequential input passed to both the Bi-LSTM and LSTM models.

2. Data Preprocessing:

→ Loads a dataset from the 'deepslice_data.csv' file.

→ Encodes categorical features using Label Encoding.

→ Encodes the 'slice Type' column using Label Encoding.

→ Splits the data into training and testing sets.

3. Model Architecture:

→ Defines a Bi-LSTM (Bidirectional Long Short-Term Memory) model for resource allocation and slice selection.

→ Defines an LSTM (Long Short-Term Memory) model for statistical information regarding network slices.

→ Concatenates the outputs of the Bi-LSTM and LSTM models.

→ Creates a hybrid model with a final classification dense layer.

3. Simulated Network Slicing Controller:

→ Defines a simulated network slicing controller (network_slicing_controller function) that allocates resources based on requested slices.

→ Simulates slice requests with specific requirements (e.g., bandwidth) and sends them to the network slicing controller.

→ Prints the simulated allocated slices.

5. Model Training and Evaluation:

→ Compiles the hybrid model with the specified loss function, optimizer, and metrics.

→ Trains the hybrid model on the training data.

→ Evaluates the model on the test set and prints the accuracy.

→ Generates predictions and prints the classification report and confusion matrix for the hybrid model.

6. Visualization:

→ Plots a heatmap of the confusion matrix for the hybrid model.

→ Visualizes resource allocation by creating a scatter plot comparing the required bandwidth with the calculated allocated bandwidth.

7. Apply OGD( online gradient descent) Algo:

→ It can be used to dynamically adjust the allocation of resources based on changing conditions or demands. So, the OGD algorithm facilitates dynamic resource allocation by continuously learning from past resource allocation decisions and adjusting its behaviour based on the current context. This adaptability allows it to respond to changing conditions and optimize resource utilization over time.

HOW OGD (ONLINE GRADIENT DESCENT) ALGORITHM WORKS?

1. **Initialization**:

➢ Initially, the OGD algorithm initializes its weights to zeros or small random values.

2. **Prediction**:

➢ Given a set of features representing the current state or context (such as network conditions, user demands, etc.), the algorithm predicts the resource allocation based on the current weights.

3. **Compute Gradient**:

- ➢ After making a prediction, the algorithm compares the predicted resource allocation with the actual allocation (target).
- ➢ It calculates the gradient of the error between the predicted and actual allocations.

4. **Update Weights**:

- ➢ Using the computed gradient, the algorithm updates its weights to minimize the prediction error.
- ➢ By adjusting the weights, the algorithm learns to better predict resource allocations based on the input features.

5. **Repeat**:

- ➢ The process iterates over each new data point or context, making predictions, computing gradients, and updating weights.
- ➢ Over time, the algorithm adapts its weights to changing conditions, improving its ability to allocate resources effectively.

6. **Resource Allocation**:

- ➢ Once the algorithm has been trained on historical data and has learned the appropriate weights, it can be used to dynamically allocate resources in real-time.
- ➢ By inputting the current context or features into the trained model, it can predict the optimal resource allocation based on the learned patterns from past data.

## IX. PEFORMANCE EVALUATION:

Accuracy of hybrid model is coming to be 99.79%

| | precision | recall | f1-score | support |
|---|---|---|---|---|
| URLLC | 1.00 | 1.00 | 1.00 | 2910 |
| eMBB | 0.82 | 1.00 | 0.90 | 6714 |
| mMTC | 1.00 | 0.51 | 0.67 | 3010 |
| accuracy | | | 0.88 | 12634 |
| macro avg | 0.94 | 0.84 | 0.86 | 12634 |
| weighted avg | 0.90 | 0.88 | 0.87 | 12634 |

Fig 2: performance evaluation of proposed hybrid model for network slicing

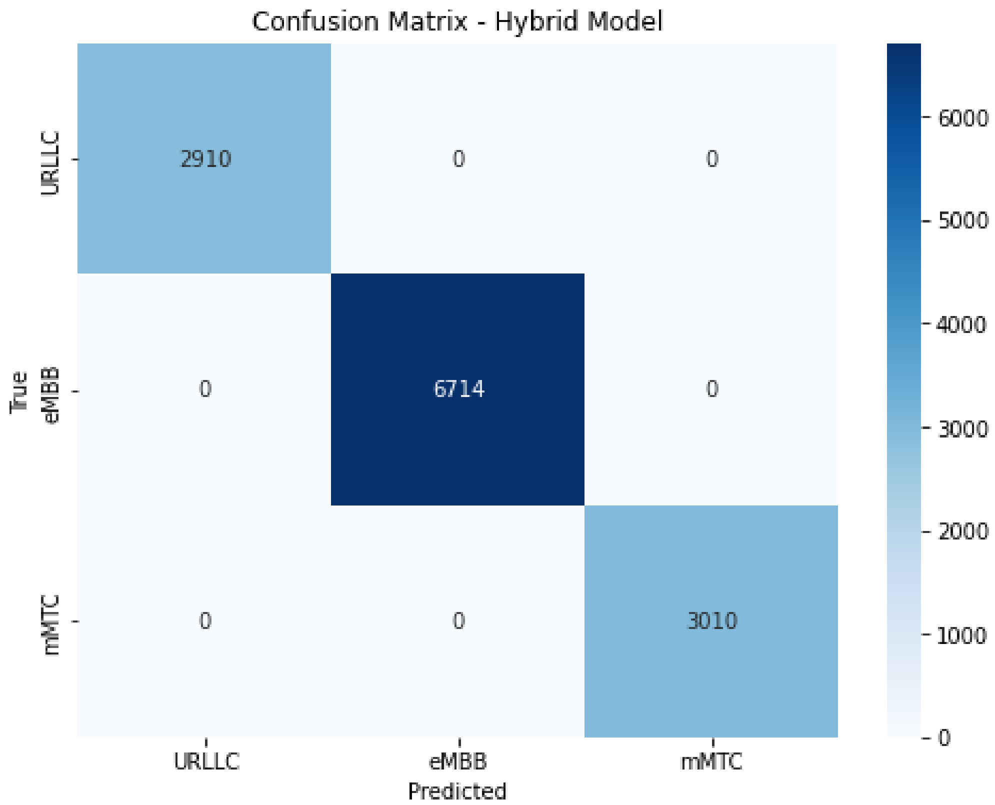


Fig 3: confusion matrix for analysing hybrid model for network classification

```
User_ID  Required_Bandwidth Allocated_Bandwidth  Resource_Allocation  \
0      User_1                 10.0                 15 Mbps                 0.70
1      User_2                100.0                120 Kbps                 0.80
2      User_3                  5.0                  6 Mbps                 0.75
3      User_4                  1.0                1.5 Mbps                 0.90
4      User_5                  2.0                  3 Mbps                 0.85
..        ...                  ...                   ...                  ...
395  User_396                  1.3                1.8 Mbps                 0.85
396  User_397                 14.5               15.8 Mbps                 0.75
397  User_398                  1.0                1.4 Mbps                 0.70
398  User_399                  0.4                0.4 Mbps                 0.70
399  User_400                  0.1                0.1 Mbps                 0.70

     Allocated_Bandwidth_Calculated
0                             7.000
1                            80.000
2                             3.750
3                             0.900
4                             1.700
..                              ...
395                           1.105
396                          10.875
397                           0.700
398                           0.280
399                           0.070

[400 rows x 5 columns]
```

Fig 4:output for non-optimized resource allocation

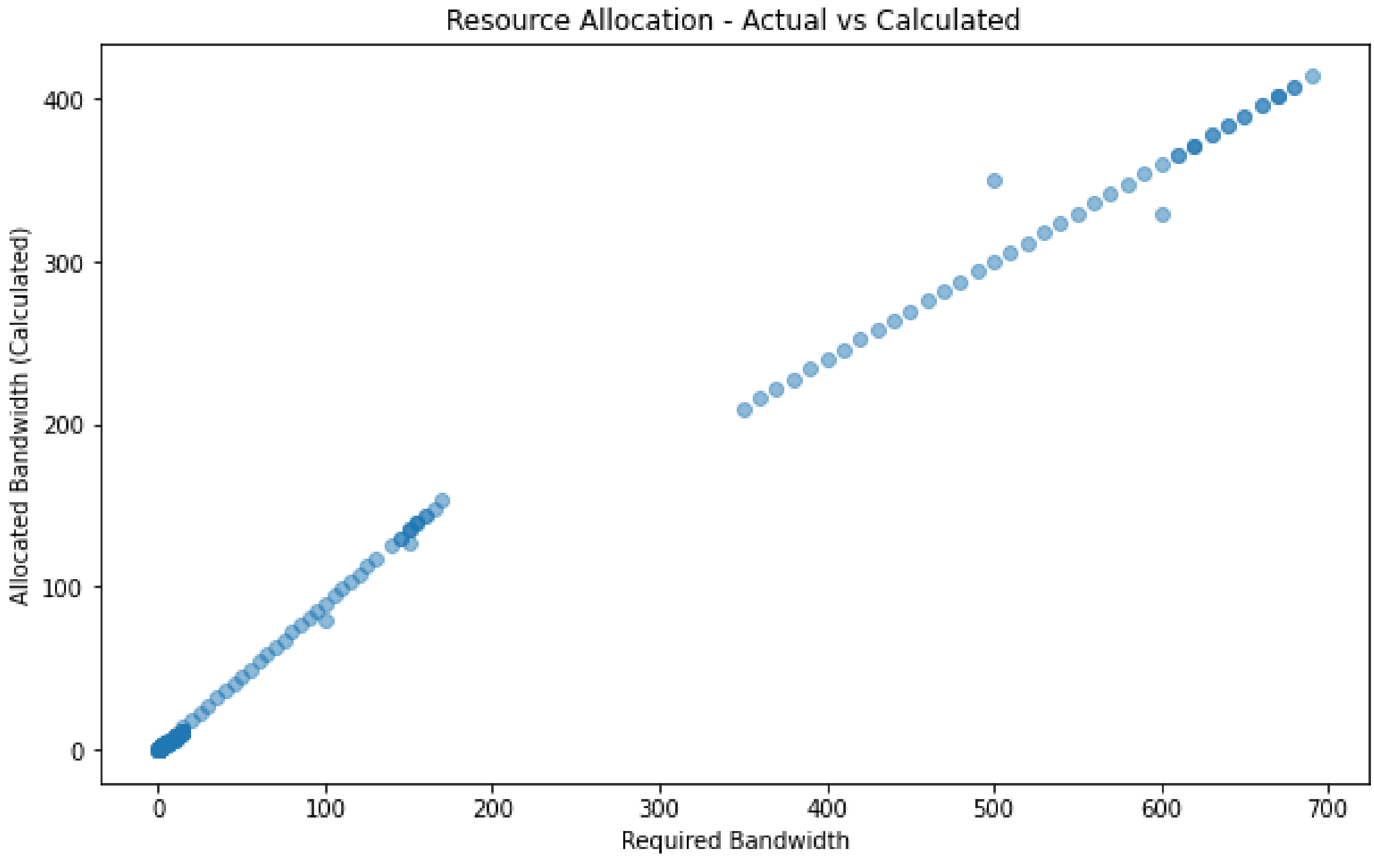


Fig 5: analysis for resource allocation being done

What does this plot infer?

→ Perfect Allocation: In an ideal scenario, all points should lie along a diagonal line, indicating that the allocated bandwidth matches the required bandwidth perfectly.

→ Under allocation: Points below the diagonal line suggest that the model is allocating less bandwidth than required. This could indicate inefficiencies or limitations in your resource allocation algorithm.

→ Overallocation: Points above the diagonal line suggest that the model is allocating more bandwidth than required. This could result in wasted resources and may need further investigation.

→ Scatter and Spread: A wider spread of points around the diagonal may indicate variability in the model's performance for different scenarios or user cases. If the spread is too wide, it might be worth exploring ways to improve the consistency of resource allocation.

→ So, the scatter plot provides a visual assessment of how well your resource allocation model aligns with the actual requirements. It helps identify patterns and deviations, enabling you to refine and improve your resource allocation strategy if needed.

```
       User_ID  Required_Bandwidth  Allocated_Bandwidth_Calculated  \
0       User_1                10.0                        7.000 Mbps
1       User_2               100.0                       80.000 Mbps
2       User_3                 5.0                        3.750 Mbps
3       User_4                 1.0                        0.900 Mbps
4       User_5                 2.0                        1.700 Mbps
..         ...                 ...                          ...
395   User_396                 1.3                        1.105 Mbps
396   User_397                14.5                       10.875 Mbps
397   User_398                 1.0                        0.700 Mbps
398   User_399                 0.4                        0.280 Mbps
399   User_400                 0.1                        0.070 Mbps

     Allocated_Bandwidth_Optimized
0                     1.904623e+24
1                     1.904623e+25
2                     9.523116e+23
3                     1.904623e+23
4                     3.809246e+23
```

Fig 6: output after optimization resource allocation

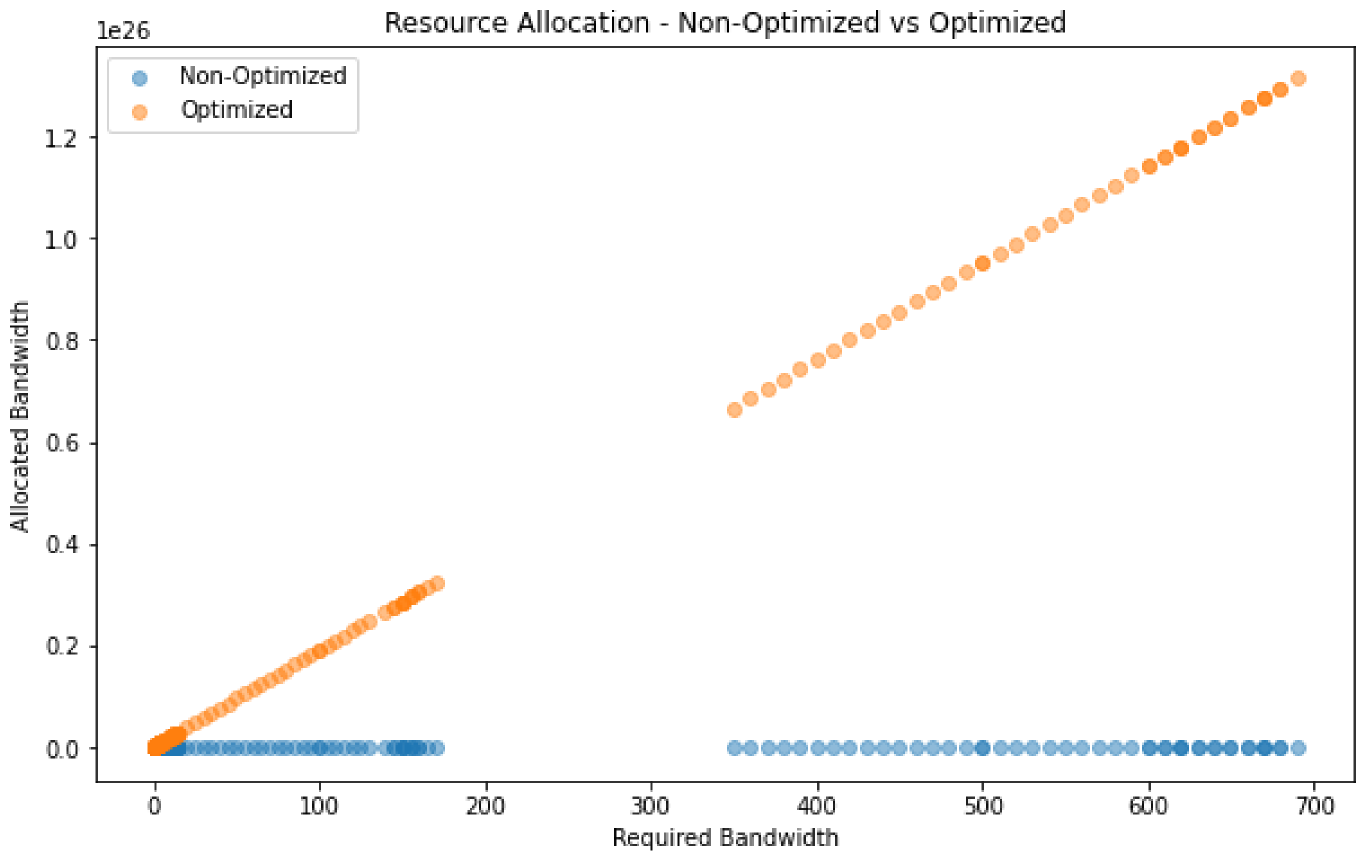


Fig 7: Resource allocation- non-optimized vs Optimized resource allocation

WHAT DOES THIS GRAPH INFER?

The graph plots the relationship between the required bandwidth and the allocated bandwidth for both non-optimized and optimized scenarios. Here is what each element of the graph represents:

- X-Axis (Required Bandwidth): This axis represents the required bandwidth for each data point in the dataset. Each point on the x-axis corresponds to a specific user or data point in the dataset.
- Y-Axis (Allocated Bandwidth): This axis represents the allocated bandwidth for each data point in the dataset.
- Non-Optimized Scatter Points: These points represent the allocated bandwidth calculated based on the non-optimized resource allocation method. Each point's position on the graph indicates the required bandwidth (x-axis) and the corresponding allocated bandwidth (y-axis) calculated using the non-optimized approach.
- Optimized Scatter Points: These points represent the allocated bandwidth calculated based on the optimized resource allocation method using the OGD algorithm. Each point's position on the graph indicates the required bandwidth (x-axis) and the corresponding allocated bandwidth (y-axis) calculated using the optimized approach.
- By comparing the distribution of scatter points between the non-optimized and optimized scenarios, the graph visually demonstrates the effectiveness of the optimization achieved through the Online Gradient Descent algorithm.

WHY WAS OPTIMIZATION REQUIRED?

Instead of a fixed scaling factor like 1.2, implementing dynamic resource allocation strategies that adapt to changing network conditions should be considered, traffic demands, and user requirements in real-time.

## X. FUTURE WORK

- Real Data Integration:
  Consider using real-world data for training and testing your models. Real data can provide more accurate insights and enhance the performance of your models.
- Hyperparameter Tuning:
  Experiment with different hyperparameter configurations for models. Fine-tuning parameters such as learning rate, batch size, and the number of epochs can significantly impact the model's performance.
- Model Architecture Exploration:
  Explore different architectures for hybrid model. Vary the number of LSTM layers, the number of units in each layer, and the activation functions to see how they affect the model's performance.

- ❖ Ensemble Methods:

  Investigate ensemble methods, where multiple models are combined to make predictions. Ensemble methods can often improve performance and robustness.
- ❖ Dynamic Network Slicing Controller:

  Enhance the simulated network slicing controller to make it more dynamic and responsive. In a real-world scenario, network conditions and requirements may change dynamically, and the controller should adapt accordingly.
- ❖ Transfer Learning:

  Explore transfer learning techniques. Models can be pre-trained on a related task or dataset and fine-tune them for specific problem. This can be especially beneficial if there is limited labeled data.
- ❖ Explainability and Interpretability:

  Implement techniques to explain and interpret the model's predictions. This is crucial, especially in scenarios where decisions need to be justified.
- ❖ Online Learning:

  Consider implementing online learning techniques, allowing the model to adapt and learn continuously as new data becomes available.
- ❖ Deployment and Integration:

  If applicable, work on deploying the models into a production environment. Consider integration with other systems and tools that are part of the larger network management infrastructure
- ❖ Advanced Visualizations:

  Enhance the resource allocation visualizations. Interactive dashboards can be created or use advanced visualization techniques to provide more insights into resource utilization.

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