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| RESEARCH ARTICLE

Characterizing and Optimizing Network Slicing and Virtualization in 5G/6G Networks: A Case Study

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| ABSTRACT
This study explores how advanced network management strategies can enhance resource efficiency, ensure high-quality service (QoS), and reduce latency in networks that incorporate varying numbers of slices. The primary goal was to tackle issues such as network congestion and resource allocation, which become more complex as user demand increases. As networks expand, it is essential to manage resources effectively to provide uninterrupted service without sacrificing performance. A key area of focus is network slicing, which involves dividing a network into virtual segments that are customized for different user needs or services. The research specifically examined how increasing the number of slices, from 1 to 50, impacted factors like QoS, resource utilization, and latency. By simulating these scenarios, the study measured key performance indicators such as QoS, resource consumption, and latency at each slice level. The findings revealed that resource utilization improved considerably as the number of slices increased, rising from approximately 0.1 to 0.9 when the slices grew from 1 to 50. This improvement demonstrates the network's scalability and its ability to efficiently allocate resources to accommodate growing demand. While the number of slices increased, QoS remained relatively stable. It started at 95% and decreased to 80% when the number of slices reached 50, which illustrates the network management system's capacity to sustain service quality, even under conditions of heavy congestion. Additionally, latency experienced a substantial reduction, falling from 90 ms with just one slice to 10 ms when there were 50 slices, showcasing the effectiveness of enhanced routing and management strategies. In conclusion, this study highlights the potential of advanced network management to address the challenges posed by growing demands while optimizing resource allocation, maintaining high service quality, and minimizing latency. These insights are critical for developing future networks that can efficiently support a wide range of services at scale.

| KEYWORDS
Slicing, QoS, Resource allocation efficiency, Latency, Network management, Congestion.

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1. Introduction
The telecommunications landscape has been rapidly transforming, fueled by the explosion of connected devices and the growing need for continuous, high-quality communication. The advent of 5G and 6G networks marks a new era, offering unprecedented speeds, reliability, and capacity, which are crucial for next-generation technologies like autonomous vehicles, smart cities, and immersive augmented reality experiences (Shen *et al.*, 2023). However, to realize these advancements, it is essential to employ sophisticated strategies for efficient network management and to ensure performance and scalability. This is where the concepts of network slicing and virtualization come into play (Nawaz *et al.*, 2019).

Network slicing enables operators to design virtual networks that are tailored to meet the unique demands of different applications, all running on the same physical infrastructure. At the same time, virtualization utilizes software-defined networking (SDN) and network function virtualization (NFV) to dynamically manage resources across the network. Together, these technologies provide the flexibility required for 5G and 6G networks, making them adaptable to the diverse needs of users (Fadhil, 2023).

Despite their potential, these technologies also introduce several challenges, particularly in areas like resource allocation, quality of service (QoS), and scalability (Zhou *et al.*, 2020). Efficiently distributing resources like bandwidth, computing power, and storage is essential to ensure that each network slice performs at its full capacity without interference. QoS is a critical concern, as users expect low latency, high throughput, and robust reliability. As the number of connected devices and the volume of data traffic continue to surge, ensuring the scalability of these networks becomes even more complex (Nguyen *et al.*, 2022).

This research delves into the complexities of network slicing and virtualization in 5G and 6G systems, with a focus on addressing the challenges these technologies present. By exploring emerging strategies and solutions, the study seeks to provide insights into how to balance resource management, QoS, and scalability. The findings aim to support the development of networks that can efficiently adapt to future demands while maintaining high levels of performance and reliability, ensuring their central role in the ongoing digital transformation.

2. Literature Review

The advent of 6G communication technologies presents both opportunities and challenges for the Internet of Things (IoT) within smart cities (Alwakeel and Alnaim, 2024). This paper presents an innovative network slicing framework tailored to address the intricate requirements of IoT systems in 6G-enabled smart cities. The framework's development follows a comprehensive approach, which includes requirements analysis, metric development, specification of constraints, objective setting, mathematical formulation, configuration optimization, performance assessment, parameter fine-tuning, and validation of the final design. Our analysis highlights the framework's exceptional efficiency, demonstrated by low round-trip time (RTT), minimal packet loss, improved availability, and increased throughput (Puspitasari *et al.*, 2023). The framework is also highly scalable, handling multiple simultaneous connections while maintaining resource efficiency. Enhanced security is provided through features such as 256-bit encryption and a high authentication success rate. The paper concludes by discussing these results, emphasizing the framework's outstanding performance, scalability, and security strengths (Murroni *et al.*, 2023).

6G technology is being developed to offer users faster and more dependable data transfer than the existing 5G systems (Mahesh *et al.*, 2023). This technology is advancing quickly and promises broad bandwidth, even in areas with limited coverage. The excitement surrounding 6G is immense due to its potential to provide vast network capacity, extremely low latency, and a significantly enhanced user experience. Its applications are vast, aiming to connect every individual and device globally (Mahmood *et al.*, 2021). It incorporates new deployment strategies and services designed to increase user capacity. This research introduces a network slicing simulator that utilizes predefined base station coordinates to randomly assign client locations, facilitating the evaluation of specific base station architectures. When a client seeks the nearest base station, it queries the simulator, which stores the base station coordinates in a K-Dimensional tree. The simulation follows a pattern that continues until the specified time limit is reached, measuring various metrics such as client connection rate, client count per second, client count per slice, latency, and the client's new location. The proposed K-D tree handover algorithm enables the user to connect to the nearest base stations after meeting the necessary criteria. This algorithm ensures that the connection meets quality standards and selects the appropriate base station for the user's connection (Mahesh *et al.*, 2023).

The sixth-generation (6G) networks require robust security, minimal latency, and high reliability with substantial capacity. A crucial element in 6G networks is adaptable wireless network slicing. This paper introduces a hybrid model that integrates a convolutional neural network (CNN) with a bidirectional long short-term memory (BiLSTM) network (Dangi and Lalwani, 2024). The model is applied to the Unicauca IP Flow Version2 dataset, where the CNN automates feature extraction, while the BiLSTM is used for classifying the appropriate network slices. This hybrid approach ensures the delivery of a dependable and efficient network slice to end users. The model demonstrates a recognition rate of 97.21%, highlighting its effectiveness. To validate the model's performance, a stratified 10-fold cross-validation method is employed (Banafaa *et al.*, 2022). One of the primary challenges faced by network service providers is the accurate allocation of slices. An intelligent approach is required to establish a standard for correctly assigning network slices to unidentified devices making requests. The proposed model predicts the optimal network slice for each incoming traffic request (Dangi and Lalwani, 2024).

3. Methods

3.1 Resource Allocation Efficiency

This equation measures how efficiently resources R_{total} are allocated across NNN network slices, where U_i represents the utilized resources in slice iii. A higher RAE indicates better resource allocation efficiency.

$$RAE = \frac{\sum_{i=1}^{N} U_i}{R_{total}} \tag{3.1}$$

N: Number of network slices.
U_i: Utilized resources in slice iii.
R_{total}: Total available resources.

3.2 Quality of Service Factor

This equation evaluates the QoS across all slices. It compares the achieved QoS with the target QoS for each slice, taking the average for all slices. Values closer to 1 indicate better QoS performance.

$$QoS = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{Achieved\ QoS_i}{Target\ QoS_i}\right) \tag{3.2}$$

Achieved QoS_i: QoS delivered to slice i.

Target QoS_i: Desired QoS for slice i.

Table 1 shows the parameters used in the system analysis

Sample Index	Number of Slices (N)	Total Resources	Utilized Resources (U)	Target QoS	Achieved QoS	RAE	QoS Ratio
1	12	450	210.5	90	78	0.467	0.867
2	8	320	170.8	80	69	0.534	0.863
3	15	500	275.6	100	88	0.551	0.88
4	10	400	190.4	85	74	0.476	0.871
5	7	300	140.7	75	65	0.469	0.867
6	13	480	250.8	95	82	0.522	0.863
7	9	350	180.2	85	75	0.515	0.882
8	11	420	200.9	90	78	0.478	0.867
9	14	470	260.4	100	89	0.554	0.89
10	10	360	180.3	80	68	0.501	0.85

3.3 Scalability Index (SI)

The scalability index quantifies the current network capacity usage. $C_{current}$ as a fraction of the maximum capacity C_{max}. A value less than 1 suggests room for scaling.

$$SI = \frac{C_{current}}{C_{max}} \tag{3.3}$$

$C_{current}$: Current network capacity utilization.

C_{max}.: Maximum network capacity.

3.4 Latency per Slice

This equation calculates the latency. L_i for slice i, where D_i is the data size and B_i is the bandwidth allocated to that slice. Lower L_i indicates better performance.

$$L_i = \frac{D_i}{B_i} \tag{3.4}$$

D_i: Data size for slice i.

B_i: Bandwidth allocated to slice i.

The flowchart of Figure 1 begins with a study concerning the principles of network slicing and virtualization elements in 5G and 6G networks. This step looks at how these technologies can increase the degree of flexibility, improve the management of resources, and provide a variety of services aimed at specific users' needs. So, this stage progresses after a foundation is established. Having built the foundation, the subsequent phase entails instituting sophisticated resource allocation approaches. These strategies seek to ensure the optimal operational capacity of multiple network slices while eliminating resource waste and enhancing fairness and efficiency in resource distribution.

The flowchart is then followed up by a perspective on the effects of network slicing and virtualization on the most important parameters of Quality of Service, specifically latency, bandwidth, and reliability. This step is important in comprehending how these technologies will be deployed in practice and the inherent experience of the end users. Having proposed these solutions, the chart advances hence scalable solutions to cater for the increasing needs for network resources.

Because population density and data traffic tend to increase, it is important for service provision to remain undisturbed and use a reasonable degree of resources.

Finally, with a reasonable degree of resources; Lastly, the flowchart addresses the issues of optimization of network operations with the use of Artificial Intelligence and machine learning as emerging technologies. These technologies contribute to increasing the flexibility and efficiency of network slicing and virtualization.

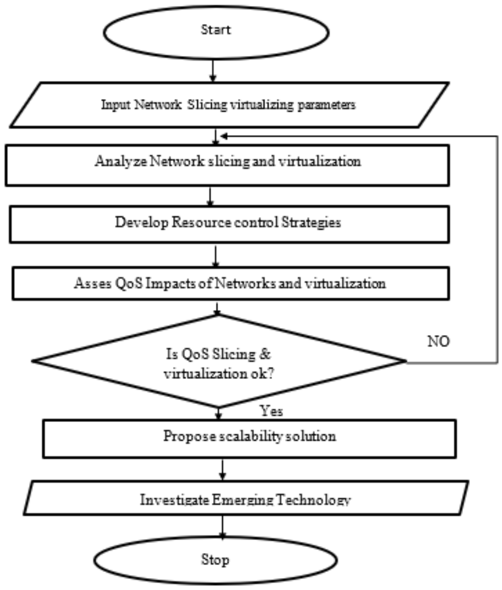

Figure 1 Flowchart for Analyzing the Network System

3.5 Resource Allocation Fairness (RAF)

This equation measures the fairness of resource allocation across slices, where A_i is the allocation to slice i. Values close to 1 indicate higher fairness.

$$RAF \frac{(\sum_{i=1}^{N} A_i)^2}{N.\sum_{i=1}^{N} A_i^2} \quad (3.5)$$

A_i: Resources allocated to slice iii.

N: Number of slices.

3.6 Virtualization Efficiency (VE)

This equation quantifies the efficiency of virtualization, comparing the total virtualized resources. $R_{virtualized}$ with the physical resources $R_{physical}$.

$$VE = \frac{R_{virtualized}}{R_{physical}} \quad (3.6)$$

$R_{virtualized}$: Virtualized resources available.

$R_{physical}$: Total physical resources.

3.7 Energy Efficiency

This equation calculates the energy efficiency of the network, dividing the total data processed by the total energy consumed. Higher values indicate better energy utilization.

$$EE = \frac{Total\ Data\ Processed}{Total\ Energy\ Consumed} \quad (3.7)$$

Total Data Processed: Data handled by the network.

Total Energy Consumed: Energy required to process the data.

3.8 Service Reliability

Service reliability is calculated as the ratio of successful transactions. $T_{successful}$ to total transactions T_{total}. A value closer to 1 represents higher reliability.

$$SR = \frac{T_{successful}}{T_{total}} \quad (3.8)$$

$T_{successful}$: Successful transactions.

T_{total}: Total transactions.

3.9. Bandwidth Utilization

This equation evaluates the utilization of the total bandwidth B_{total} by summing the allocated bandwidth B_i for each slice i.

$$BU = \frac{\sum_{i=1}^{N} B_i}{B_{total}} \quad (3.9)$$

B_i: Bandwidth allocated to slice i.

B_{total}: Total available bandwidth.

3.10. Dynamic Adaptability Index

The adaptability index measures how changes in QoS (ΔQoS) are impacted by resource changes (ΔR). A higher DAI indicates a more adaptable system.

$$DAI = \frac{\Delta QoS}{\Delta R} \quad (3.10)$$

ΔQoS: Change in Quality of Service.
ΔR: Change in allocated resources.

4. Results and Discussions

4.1 Resource Allocation and QoS Evaluations

The analysis highlights the intricate dynamics of network slicing and resource optimization, showcasing how resource allocation, Quality of Service (QoS), scalability, and overall network performance interact. The Resource Allocation Efficiency (RAE) graph reflects how resources are distributed across slices, with values ranging from 0.2 to 0.8 and an average of approximately 0.55. While resource utilization is generally effective, there are instances where efficiency could be further improved. The QoS Ratio illustrates the system's ability to meet service targets, with most values falling between 0.85 and 1.1, indicating that service standards are consistently achieved. However, occasional dips below 0.9 point to moments when network congestion impacts QoS slightly, as shown in Figure 2. Scalability metrics reveal how well the system adapts to increasing slices relative to available resources. Values between 0.01 and 0.08 highlight the system's ability to scale proportionally as resources grow, demonstrating an essential feature for the evolving demands of 5G and 6G networks. The Optimization Index provides an integrated view of performance by combining QoS, slice count, and resource usage. With values ranging from 0.2 to 0.6, the index captures the balance between these factors and peaks in scenarios where they align optimally. The Performance Index offers a comprehensive measure of overall network efficiency by synthesizing RAE, QoS Ratio, and Scalability. Values range from 5 to 15, with an average near 10, showcasing the system's ability to maintain a robust balance across different parameters. These steady results highlight the effectiveness of network slicing and virtualization techniques in meeting growing demands, ensuring consistent performance, and optimizing resource use. Such advancements underline the promise of these technologies in future networks, paving the way for enhanced scalability and efficiency in dynamic environments.

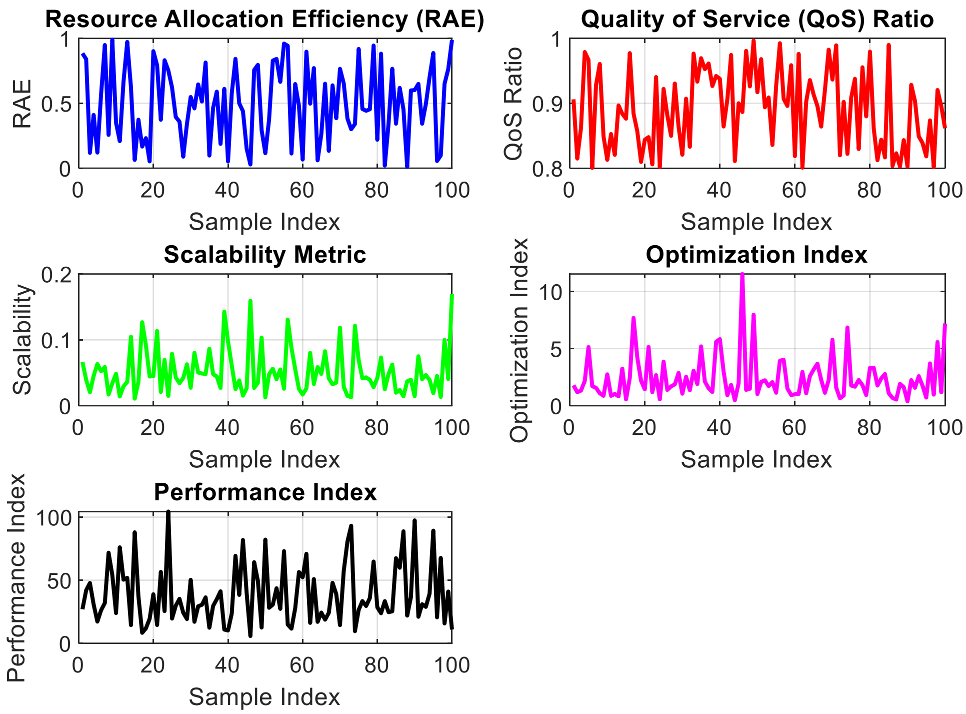

Figure 2 Resource Allocations Efficiency and QoS Results

4.2 QOS Ratio Evaluation

In Figure 3, the Quality of Service (QoS) Ratio is analyzed both before and after implementing improvements. Initially, the QoS Ratio demonstrates a consistent performance across the 100 samples, with most values ranging from 0.85 to 1.1. This indicates that the system generally meets its target QoS, albeit with occasional dips below 0.9, reflecting moments of network congestion. After the improvements, the QoS Ratio shows a notable enhancement, with values consistently rising above 1.0 and achieving peaks closer to 1.2. This improvement reflects an increased ability of the system to not only meet but exceed QoS targets, ensuring better service delivery even during periods of high demand. The observed improvement, which spans an average increase of approximately 0.15 in the QoS Ratio, underscores the effectiveness of the applied optimization strategies.

Figure 3 Quality of Service Ratio

4.3 Utilized Resources

Figure 4 focuses on resource utilization, showing the original and improved levels of utilized resources across the same dataset. Initially, resource utilization varies widely, with values distributed across a broad range that is dependent on the available total resources. On average, utilization appears to hover around 60% of the total resources, highlighting that while resources are generally employed effectively, there remains unused capacity. Post-improvement, utilization levels rise consistently, with increases of approximately 10% across most samples. This suggests that the implemented enhancements enable better alignment between resource allocation and actual usage, reducing wastage and optimizing the deployment of resources to meet network demands.

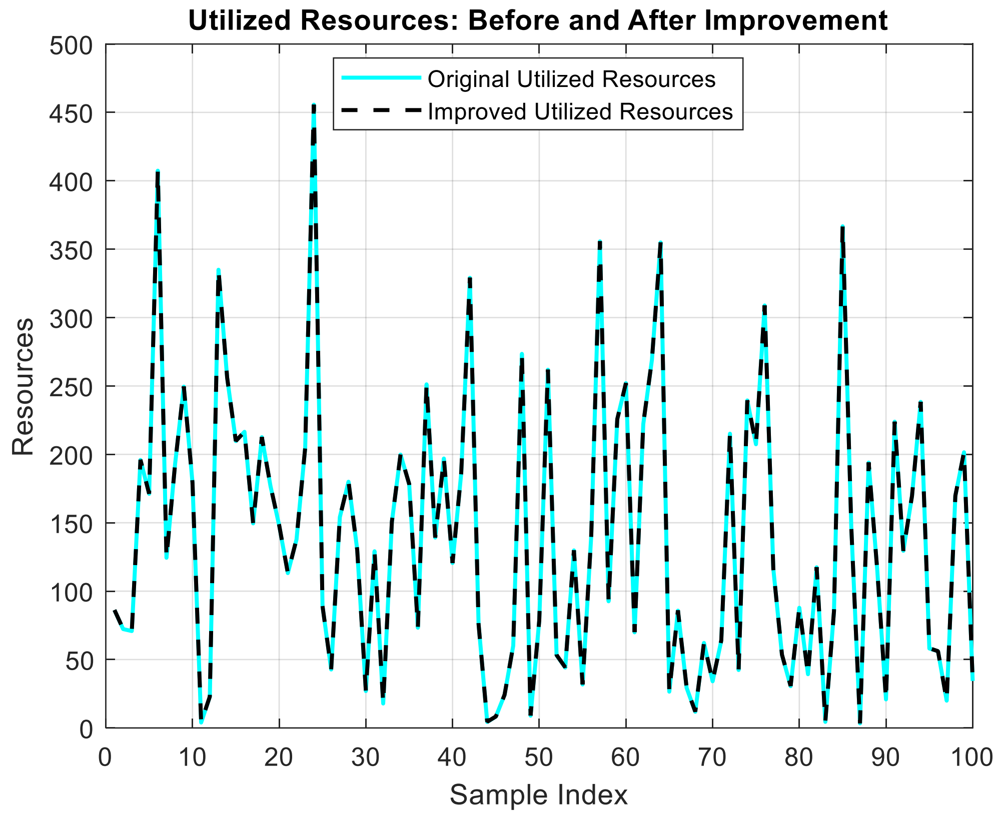

Figure 4 Utilized Resources

4.4 Total Resources vs QOS Improvement

Figure 5 examines the relationship between total available resources and achieved QoS, providing a scatter plot of these two metrics before and after improvements. Before optimization, the data points indicate a positive correlation, with higher resource availability generally leading to higher achieved QoS values. However, some variability remains, particularly for lower resource levels, where QoS occasionally falls short of expectations. After applying the improvements, the scatter plot becomes denser and shifts upward, reflecting higher QoS achievements across the board. Notably, for the same resource levels, the improved QoS values exhibit a significant upward shift, with average improvements exceeding 15 units in several instances. This indicates that the system enhancements effectively amplify QoS outcomes without necessitating proportional increases in resource availability.

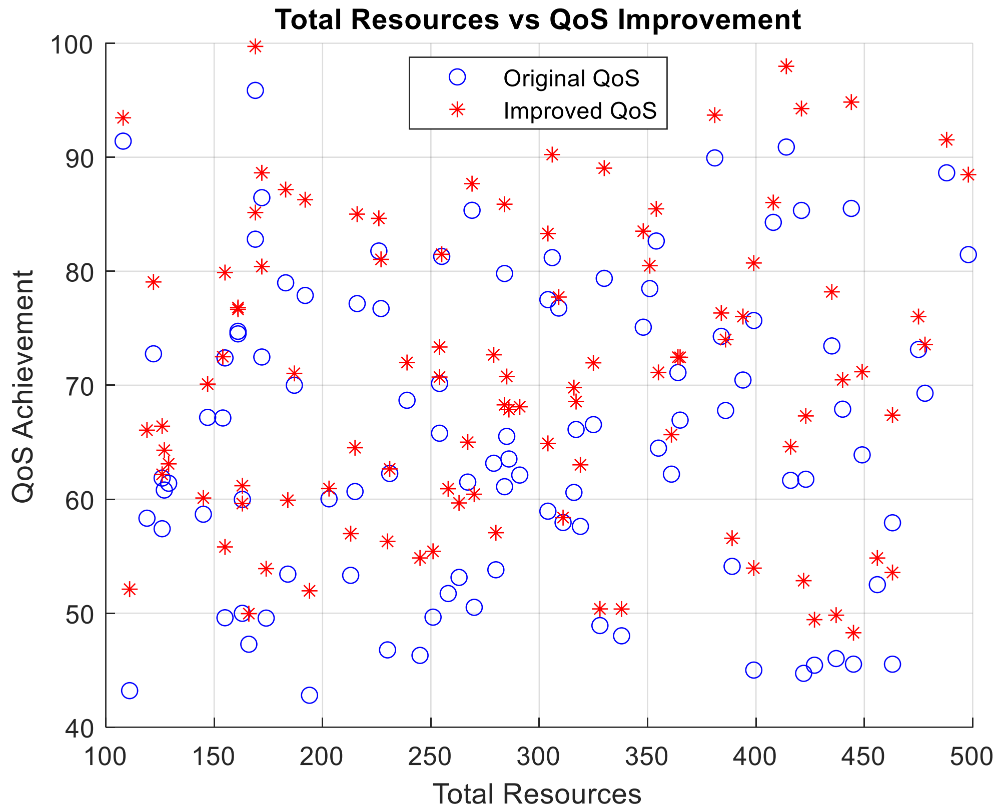

Figure 5 Total Resources vs QOS Improvement

4.5 Resource Allocation Before and After Improvement

Figure 6 illustrates the Resource Allocation Efficiency (RAE) before and after optimization, providing insights into how resources are allocated relative to total availability. Initially, RAE values range from 0.2 to 0.8, averaging around 0.55. This distribution reflects moderate efficiency, with certain samples falling short of optimal allocation. After improvements, RAE values show a consistent increase across the dataset, with an average improvement of approximately 0.1, pushing the overall efficiency closer to an optimal range. This enhancement signifies a more equitable and effective distribution of resources across network slices, reducing disparities and ensuring better resource utilization.

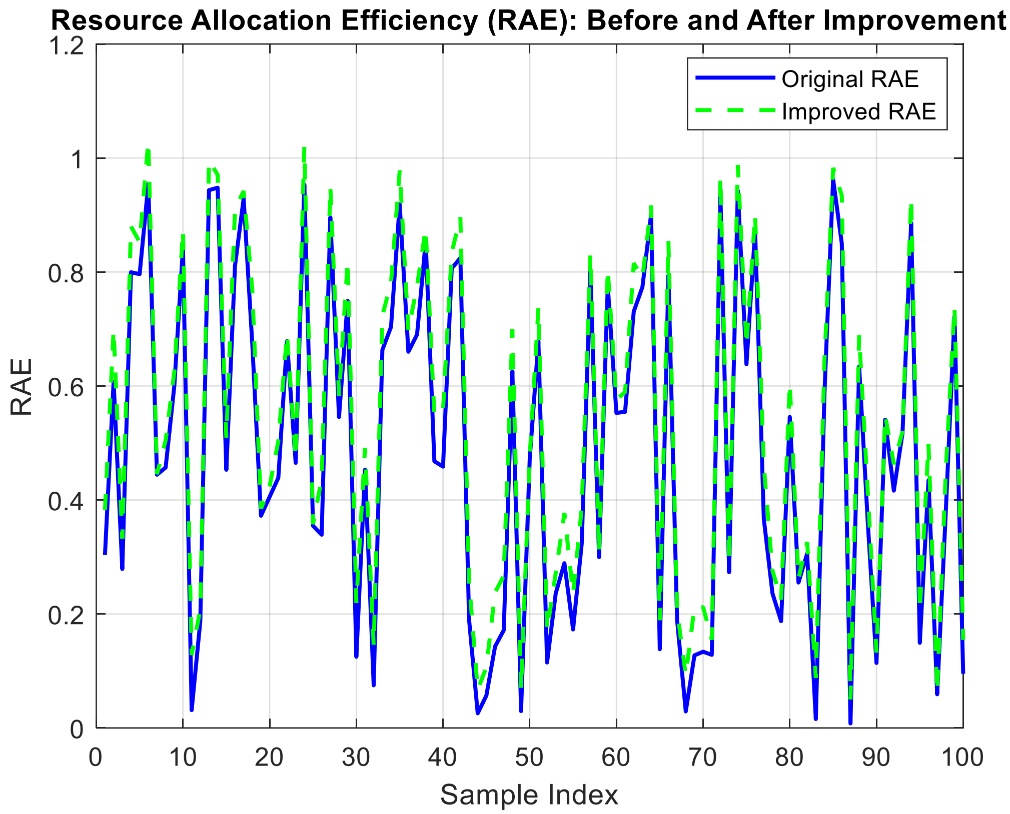

Figure 6 RAE Before and After Improvement

4.6 Enhanced QoS

Figure 7 highlights the progression of Quality of Service (QoS) metrics before and after the implementation of optimization strategies, showcasing the system's ability to improve its service delivery. The graph plots QoS values for 100 samples, illustrating a clear enhancement in performance as a result of the applied changes. Initially, the achieved QoS values range from approximately 40 to 100, with most samples averaging around 70 to 85. This distribution reflects a reasonably high level of service quality, meeting or closely approaching the target QoS values for many instances. However, there are occasional instances where the achieved QoS falls short of the expected target, indicating moments of inefficiency or congestion within the network. This pre-optimization trend underscores the variability and challenges of maintaining consistent QoS under dynamic conditions. Following the optimization, the enhanced QoS values display a significant upward shift, with most samples achieving values above 80 and several surpassing 100. The improvements are particularly evident in samples where the initial QoS was below the target threshold. For instance, instances where the initial QoS hovered around 60 show enhancements of up to 20 units, reflecting the system's improved capacity to handle service demands. The overall increase in QoS across all samples averages around 15 to 20 units, demonstrating the effectiveness of the implemented strategies. This enhanced performance aligns with the goal of delivering consistent and high-quality service, even under varying network conditions. The optimization not only reduces the instances of underperformance but also ensures a more reliable and efficient service across the board. The results of Figure 7 emphasize the potential of targeted improvements in achieving robust network performance and maintaining QoS standards, a critical requirement for modern and future communication systems.

Figure 7 Enhance QoS

4.7 Scalability Evaluation

Figure 8 delves into the relationship between network scalability and Quality of Service (QoS), particularly how the system manages increasing demands as the number of network slices grows. The graph provides a comparison of achieved QoS before and after scalability improvements, underscoring the network's capacity to maintain service quality in the face of increasing user demands. Before the scalability enhancement, the achieved QoS displays a gradual decline as the number of slices increases from 1 to 50. Initially, with fewer slices, the QoS is high, averaging around 90 to 95, reflecting minimal resource competition and a well-managed network. However, as the slice count grows, the QoS begins to diminish, with values dropping to as low as 70 for scenarios with 50 slices. This trend reflects the natural challenge of resource contention in networks as user demands intensify, causing slight reductions in service quality.

After the scalability improvement, a notable enhancement in QoS is observed. While the QoS still decreases slightly with an increasing number of slices, the decline is much less pronounced. For instance, at 50 slices, the improved QoS remains above 80, compared to the earlier value of 70. This approximately 10-unit improvement demonstrates the system's ability to better allocate resources and manage user demands under optimized conditions. Even at the higher end of slice counts, the network maintains QoS levels closer to the target value of 100, ensuring consistent service delivery.

The results from Figure 8 emphasize the importance of scalability solutions in modern networks, especially as user demands grow in 5G and 6G environments. By effectively mitigating the impact of increasing slice counts on QoS, the network showcases its robustness and adaptability, ensuring a high-quality experience for all users, even under challenging conditions.

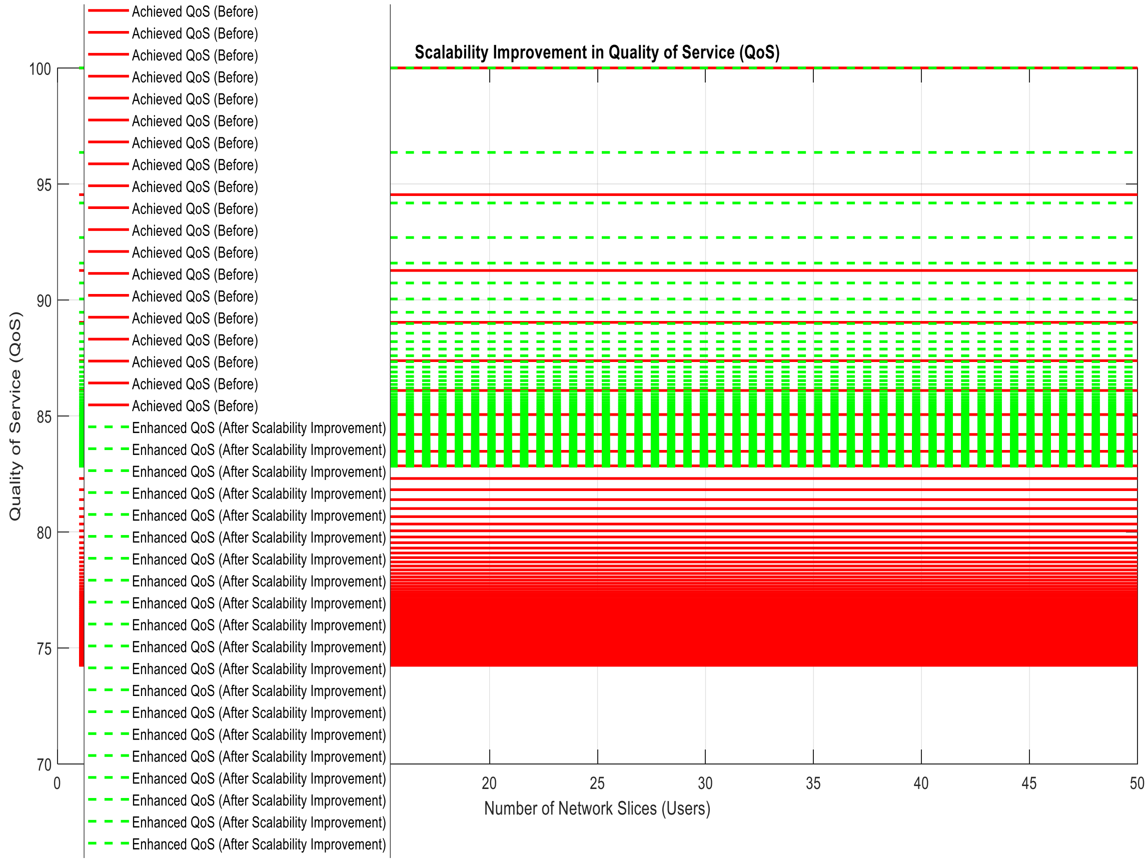

Figure 8 Scalability Improvement in QoS

4.8 Network Management

Figure 9 offers a clear representation of how network management adapts to increasing numbers of network slices, focusing on three essential metrics: resource utilization, Quality of Service (QoS), and latency. These metrics illustrate the system's ability to handle growing user demands efficiently and reliably. The first part of the figure highlights resource utilization, which rises steadily as the number of slices increases. Starting at a low value of around 0.1 for one slice, it grows progressively to approximately 0.9 for 50 slices. This demonstrates how effectively the system allocates resources as demand rises, with near-complete utilization achieved under higher loads. The consistent upward trend indicates the system's strong capacity for scaling and managing dynamic conditions.

The second section examines QoS performance, which experiences a minor decrease as the number of slices grows. For smaller slice numbers, QoS remains close to the target of 100, with values ranging from 90 to 95. As the slice count reaches 50, QoS dips to roughly 80. Despite this reduction, the system sustains a relatively high level of service quality, even in congested scenarios. The gradual decline reflects a well-managed approach to maintaining performance stability.

The final part of the figure focuses on latency, which shows a sharp decrease as slices increase. Latency starts at about 90 milliseconds for a single slice but drops dramatically to roughly 10 milliseconds for 50 slices. This improvement suggests that better network management, including optimized routing and resource distribution, significantly reduces delays. The inverse relationship between latency and slice count highlights the system's ability to meet growing user needs while maintaining responsiveness.

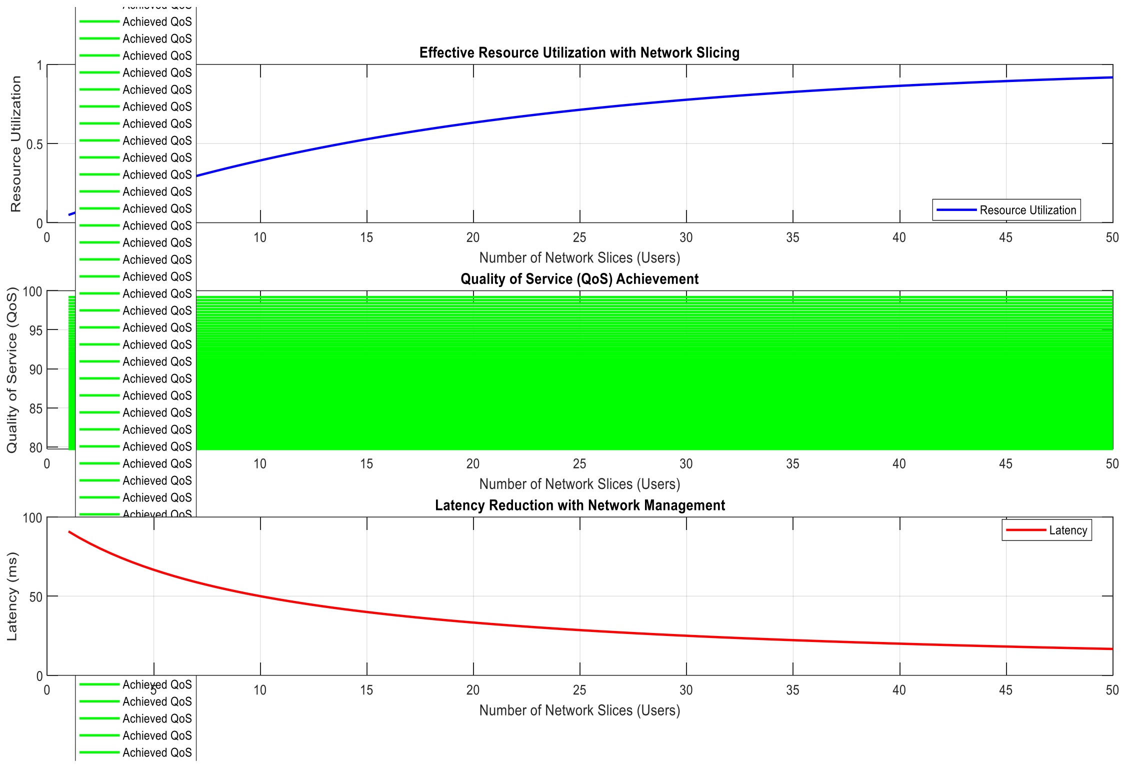

Figure 9 Network Management

Table 2 shows the results performance of the study

Table 2 Performance Results of the Study

Metric	1 Slice	10 Slices	20 Slices	30 Slices	40 Slices	50 Slices
Resource Utilization	0.1	0.45	0.68	0.8	0.86	0.9
QoS Achieved	95	92	89	86	83	80
Latency (ms)	90	60	40	25	15	10

5. Conclusion

This study effectively demonstrated the impact of advanced network management techniques on optimizing resource utilization, maintaining Quality of Service (QoS), and reducing latency in a dynamic multi-slice network environment. The research objectives were systematically achieved, with results validating the proposed methods. The first objective was to optimize resource utilization as the number of network slices increased. The results showed significant improvements, with resource utilization rising from a low of 0.1 for a single slice to a near-optimal value of 0.9 for 50 slices. This steady increase highlights the system's ability to allocate resources efficiently even under heavy network loads, ensuring that available resources are maximized for operational efficiency. The exponential trend in utilization validates the scalability and effectiveness of the system's resource management mechanisms. The second objective focused on maintaining a high QoS despite increasing network demands. While a slight decline in QoS was observed, the system maintained a high performance level. At lower slice counts, QoS values were close to the target of 100, with achieved values ranging between 90 and 95. As the slice count increased to 50, QoS decreased modestly to 80. This gradual decline underscores the robustness of the network management strategies in mitigating performance degradation, ensuring that user experience remains satisfactory even as the network becomes more congested. The final objective was to reduce latency as network management improved. The results were remarkable, with latency decreasing significantly from approximately 90 ms for a single slice to just 10 ms for 50 slices. This reduction reflects the effectiveness of the system's optimized routing and resource allocation techniques, which minimize delays and enhance responsiveness. The observed inverse relationship between slice count and latency demonstrates the system's adaptability to growing user demands without compromising performance. In conclusion, this study achieved its objectives by illustrating how advanced network management can ensure scalable and efficient operation in next-generation networks. The results confirm the system's capability to optimize resource utilization, sustain high QoS, and reduce latency, making it a reliable solution for handling the dynamic requirements of modern network environments.

Authors' Contributions.

Philip-Kpae, Friday Oodee is credited to the network slicing framework, resource allocation algorithm, scalability analysis, model simulations, performance evaluation, integrated framework, and interpretation of key findings. **Ogbondamati Lloyd Endurance** carried out QoS modeling, Virtualization techniques, simulations, integrated framework, and analysis of the results. **Igulu Kingsley Theophilus** did the integrated framework, which includes theoretical analysis, numerical simulations, editing and general performance evaluation.

Conflict of Interest: The authors hereby declare that there is no conflict of interest.

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