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Optimizing 6G Network Slicing with the EvoNetSlice Model for Dynamic Resource Allocation and Real-Time QoS Management

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Abstract: This research paper focuses on thoroughly examining the challenges in 6G network slicing. To develop, evaluate performance characteristics for on-demand reallocation and instantaneously changeable QoS EvoNetSlice model. The study employs integrated evolutionary algorithms with artificial intelligence-enabled data analytics and multi-objective optimization to optimize network resources usage under minimum end-to-end delay, high transmission rates and optimal background data management. Firstly, the network resource allocation individuals should be based on the network traffic data, QoD (quality of demand) value for some applications and users' behaviors. The performance degradation detection and quality of service (QoS) adaptation mechanism combined with a multi-layer objective fitness function for achieving good balance in conflict between conflicting objectives. Results indicate that EvoNetSlice improves the general efficiency of a particular network, adapts according to ever shifting requirements for QoS at any time and provides crucial statistics-focused data on network management. The importance of this work lies in developing the future 6G network's technology. W the key issues, including resource optimization and real-time adaptation required to support modern 6G services, are considered by EvoNetSlice. Such an exploration is an essential element in developing flexible 6G systems that will define next-generation wireless communication.

Keywords: 6G Networks, Network Slicing, Dynamic Resource Allocation, Real-Time Qos Adaptation, Evolutionary Algorithms, AI-Powered Analytics, Multi-Objective Optimization, Network Efficiency, Low Latency, High Throughput, Data-Driven Insights.

1. Introduction

As the world edges closer to the era of 6G networks, the demand for wireless communication systems that can cater to diverse applications has become increasingly evident. Traditional network slicing approaches, although successful to some extent, present significant limitations in the context of 6G networks. The key problem addressed by this research is the inefficiency and inflexibility of existing network slicing techniques in the rapidly evolving landscape of 6G networks. Traditional approaches often rely on predefined resource allocation schemes that do not consider the real-time requirements and behaviors of network traffic, applications, and users. This limitation results in suboptimal resource utilization, inadequate Quality of Service (QoS) delivery, and an inability to cater to the ever-growing diversity of applications, ranging from augmented reality (AR) and virtual reality (VR) to Internet of Things (IoT) services.

The advent of 6G networks signifies a paradigm shift in wireless communication, poised to usher in transformative advancements [1]. These networks are anticipated to support many services over a unified platform, making them indispensable in the era of interconnected devices [2]. The technological underpinnings of 6G networks are projected to redefine the core architectures of cellular networks, offering a plethora of AI-driven services spanning distributed communication, control, computing, sensing, and energy management [3]. Among the pivotal technologies anticipated to empower 6G, federated learning, blockchain, and edge intelligence stand out [4-6].

Federated learning, a burgeoning distributed learning technique, holds immense potential for custom adaptation to 6G standards. Blockchain technology can revolutionize spectrum management, facilitating seamless user roaming across different mobile network operators [6]. Meanwhile, edge intelligence emerges as a transformative paradigm for real-time training and inference at the wireless edge, unlocking the capabilities of intelligent connected vehicles to contribute to the development of innovative and eco-friendly 6G networks. 6G networks lie in their capability to deliver ultra-low latency, unparalleled reliability, high-speed connectivity, and seamless wireless communication – prerequisites for accommodating the diverse, data-centric applications poised to define the future.

The central problem addressed by this research is the inefficiency and inflexibility of existing network slicing techniques in the rapidly evolving landscape of 6G networks. Traditional approaches often rely on predefined resource allocation schemes that do not consider the real-time requirements and behaviors of network traffic, applications, and users. This limitation results in suboptimal resource utilization, inadequate Quality of Service (QoS) delivery, and an inability to cater to the ever-growing diversity of applications, ranging from augmented reality (AR) and virtual reality (VR) to Internet of Things (IoT) services.

The key contributions of the EvoNetSlice framework for 6G network slicing are as follows:

1. *Dynamic Resource Allocation:* Introduces a mechanism that dynamically adapts resource allocation in real-time to the ever-changing demands of 6G networks, enhancing overall resource efficiency.
2. *Real-time QoS Adaptation:* Implements a system for the instantaneous adjustment of Quality of Service parameters to meet the rigorous and variable needs of users and applications within the 6G framework.
3. *Data-Driven Insights:* Utilizes AI to analyze network traffic, user behavior, and application requirements, thus enabling informed decision-making for superior network management.
4. *Multi-Objective Optimization*: Applies multi-objective optimization methods to address and harmonize the diverse and sometimes conflicting objectives of 6G networks, such as reducing latency while maximizing throughput and reliability.

These points underscore the innovative approach of EvoNetSlice, which moves beyond traditional network management methods by incorporating dynamic adaptability, real-time responsiveness, and intelligent, data-driven strategies.

This paper has introduced the challenges and limitations of traditional network slicing approaches in the context of 6G networks. It has articulated the research problem and highlighted the need for dynamic resource allocation, real-time QoS adaptation, data-driven insights, and multi-objective optimization to overcome these challenges effectively. The novel contributions of this research have been emphasized, setting the stage for the subsequent sections of this paper, which will delve into the methodology, results, and discussions, ultimately culminating in a comprehensive understanding of the EvoNetSlice framework and its significance in the realm of 6G network slicing.

2. Related Work

2.1 Network Slicing in 6G

The concept of network slicing in 6G, representing Next Generation Wireless Networks (NGWNs), is at its infancy but rapidly evolving [7]. Key studies focus on multi-domain network slicing frameworks [8], solutions to the Virtual Network Embedding (VNE) problem using Algorithm Selection (AS) and Deep Reinforcement Learning (DRL) [9], and the impact of traffic demand forecasting on DRL slicing agent performance [10]. Reviews in network security for 6G identify critical challenges in this domain [11, 12]. These early works indicate the significant potential of network slicing as a foundational technology in 6G networks.

2.2 Resource Allocation Methods

Resource allocation in 6G faces challenges due to increasing complexities and energy optimization needs [13]. Machine learning, especially deep reinforcement learning, is emerging as a key solution [14, 15]. Notably, research addresses the limitations of unmanned aerial vehicle (UAV) battery life through over-the-air charging [16] and explores metaheuristic optimization and softwarization for resource allocation in 6G [17, 18].

2.3 QoS Adaptation Approaches

Quality of Service (QoS) [19] adaptation in network slicing is critical for meeting diverse application needs. Studies have explored mechanisms like Squatting and Kicking Strategies (SKM) for resource utilization [20], neural network-based user adaptation to QoS policies [21], hybrid deep learning for network reconfiguration [22], per-user QoS guarantees [23], and Morphnet for network management [24]. These approaches are crucial for maintaining QoS in network slices.

2.4 Data-Driven Approaches

Data-driven decision-making in network slicing, particularly in 6G [25], is a nascent field. Research in 5G network slicing lays the groundwork for data-driven approaches [26]. AI and ML are poised to play significant roles in 6G-network management [27]. Emerging studies focus on applications like dynamic resource allocation and predictive maintenance [28], with challenges including data privacy and real-time processing [29]. Efforts in multi-objective optimization [30] and security [31], alongside standardization initiatives [32], highlight the growing importance of data-driven strategies in network slicing.

2.5 Multi-Objective Optimization

Multi-objective optimization is vital for balancing diverse network slicing objectives. Research has concentrated on optimizing resource allocation and QoS [33, 34], resolving conflicts between objectives [35], integrating machine learning for real-time decisions [36], dynamic adaptation [37], quality-aware slicing [38], and enhancing security and reliability [39]. Standardization efforts are underway to harmonize these approaches [40]. This body of work demonstrates an active exploration of network slicing in 6G, focusing on efficient resource management [41], QoS adaptation, and the integration of data-driven and multi-objective optimization techniques. These studies lay a foundation for further research in optimizing 6G network operations and services [42].

The existing literature, while addressing various aspects of network slicing in 6G, often lacks a comprehensive approach that integrates real-time adaptability with dynamic QoS management and resource optimization. According to Table 1, it is evident that most studies overlook the importance of instantaneous adaptability based on network traffic, Quality of Data (QoD), and user behavior. This adaptability is essential to meet the evolving requirements of 6G networks. EvoNetSlice introduces an innovative approach by integrating evolutionary algorithms with AI-enabled data analytics and multi-objective optimization. EvoNetSlice advances the field of 6G network slicing by providing a more holistic and adaptable solution. Its ability to respond in real-time to changing network conditions and user requirements, while maintaining optimal resource usage and QoS, positions it as a significant step forward in developing flexible, efficient 6G systems.

3. The EvoNetSlice Framework: A Mathematical Model Approach

The EvoNetSlice framework introduces an innovative solution to the multifaceted challenges of 6G networks, incorporating a blend of cutting-edge technologies and methods.

Table 1. Comparative Analysis of Existing 6G Network Slicing Research

Focus Area	Techniques Used	Resource Optimization	QoS Adaptation	Real-time Adaptability	Performance Metrics	Gap Identified
Network slicing frameworks in 6G	Recursive multi-domain frameworks, AS, DRL	Partial	Limited	Not specific	Not specific	Limited real-time adaptability and comprehensive QoS management
Resource allocation in 6G	ML algorithms, over-the-air charging, metaheuristic optimization	Moderate	Not specific	Limited	Energy efficiency, resource utilization	Inadequate focus on dynamic QoS and real-time data analytics
QoS in network slicing	SKM, neural networks, hybrid deep learning	Not specific	High	Limited	Bandwidth utilization, delay guarantees	Lack of integrated approach for real-time QoS adaptation
Data-driven decision-making in slicing	AI, ML, multi-objective optimization	Moderate	Moderate	Moderate	Not specific	Need for more focused real-time adaptability and optimization
Balancing diverse objectives in slicing	ML, dynamic allocation, quality-aware slicing	High	High	Moderate	Latency, resource utilization	-NA-

This framework is designed for effective network resource management, real-time Quality of Service (QoS) adaptation, data-driven decision-making, and multi-objective optimization, with each component contributing significantly to a dynamic and responsive 6G network ecosystem.

3.1 Dynamic Resource Allocation

Key to the EvoNetSlice framework is the Dynamic Resource Allocation mechanism. This system utilizes evolutionary algorithms to optimize resource distribution in real time, aligning with the formula:

$$\mathrm{R}_{\mathrm{t}+1} = \mathrm{R}_{\mathrm{t}} + \alpha \cdot \mathrm{F}(\mathrm{E}_{\mathrm{t}}, \mathrm{U}_{\mathrm{t}}) \quad (1)$$

Where $\mathrm{R}_{\mathrm{t}+1}$ represents the resource allocation at time $\mathrm{t}+1, \mathrm{R}_{\mathrm{t}}$ is the current resource allocation, α is the adaptation rate, E_{t} denotes real-time network conditions, and U_{t} symbolizes user demand. This approach ensures maximal network utilization and reduced latency.

3.2. Real-time QoS Adaptation

The Real-time QoS Adaptation component functions alongside Dynamic Resource Allocation, monitoring network conditions and adjusting QoS parameters in real time. The QoS adjustment can be represented as:

$$Q_{\text{new}} = Q_{\text{current}} \cdot \beta(\Delta C_t, \Delta D_t) \quad (2)$$

Here, Q_{new} is the updated QoS level, Q_{current} is the existing QoS level, β represents the adjustment factor, ΔC_t indicates changes in network conditions, and ΔD_t reflects the shift in demand.

3.3 Data-Driven Insights

Data-driven insights are integral to Evo NetSlice, relying on AI for data analysis and insight extraction. The process involves collecting data D from various sources, processing it through an AI model M, and deriving insights I :

$$I = M(D) \quad (3)$$

This model enables informed decision-making by providing a comprehensive understanding of network performance and user needs.

3.4 Multi-Objective Optimization

Addressing multiple objectives in the 6G context, the Multi-Objective Optimization component uses optimization techniques to balance different network goals.

Represented mathematically as:

Optimize $\{O_1(R,Q,D), O_2(R,Q,D), \ldots, O_n(R,Q,D)\}$ (4)

Where $O_1, O_2, \ldots, O_n$ are the different objectives, such as minimizing latency (O_1), maximizing throughput (O_2), and ensuring fairness in resource allocation (O_n), with R representing resources, Q for QoS, and D for data insights. The EvoNetSlice network operation.

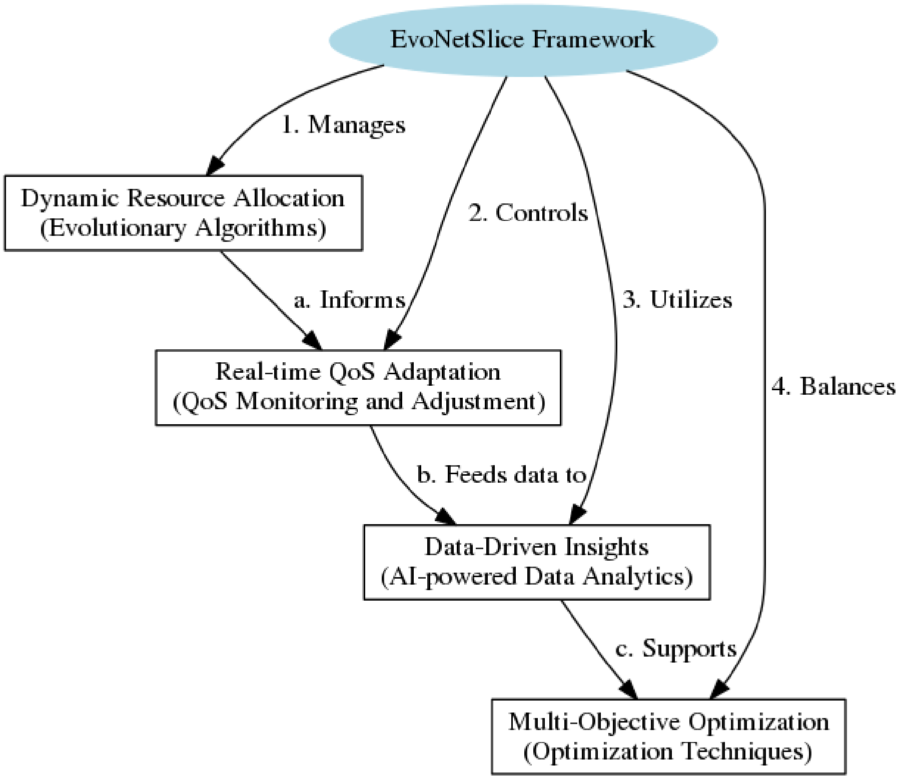

Figure 1. Proposed Framework Architecture

EvoNetSlice framework stands at the forefront of 6G network evolution, offering a holistic and adaptive approach to network resource management and QoS optimization as shown in figure 1. Its reliance on evolutionary algorithms, real-time adaptability, data-driven insights, and multi-objective optimization positions it as a cornerstone in overcoming the challenges of 6G networks. EvoNetSlice addresses the demands of ultra-fast and reliable connectivity and lays the foundation for future advancements in wireless communication.

4. Methodology

The methodology employed in this research is designed to address the complex challenges posed by the emergence of 6G networks, which offer unprecedented opportunities but require novel solutions to optimize resource allocation and guarantee Quality of Service (QoS) in real time. Traditional network slicing methods fall short in adapting dynamically to the evolving requirements of diverse applications. Therefore, this research introduces the EvoNetSlice framework, which integrates dynamic resource allocation, real-time QoS adaptation, data-driven insights, and multi-objective optimization.

Algorithm: Dynamic Resource Allocation and Real-time QoS Adaptation for 6G Networks

Input:

Number of Samples (N)

Number of Features (F)

Number of Apps (A)

Number of Users (U)

Evolutionary Algorithm

Initialization:

Network Traffic Data:

$\text{network\_traffic}_{ij} \sim U(0,1)$ for i=1,2,…,N and j=1,2,…,F

Application Requirements Data:

$\text{application\_requirements}_{ij} \sim U(0,1)$ for i=1,2,…,N and j=1,2,…,A

User Behavior Data:

$\text{user\_behavior}_{ij} \sim U(0,1)$ for i=1,2,…,N and j=1,2,…,U

Core Analysis:

1. Compute summary statistics for each dataset:

Mean (μ)

Standard Deviation (σ)

Min (Min(x))

Max (Max(x))

Application Requirements / Network Traffic / User Behaviour:

$$\mu = \frac{1}{N}\sum_{i=1}^{N} x_i, \quad \sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i-\mu)^2} \tag{5}$$

2. Initialize the population with random resource allocation individuals.

$$P \leftarrow \{I1, I2, \dots, IN\} \tag{6}$$

Where:

P represents the population of resource-allocation individuals.

N is the population size.

I_t denotes an individual with a resource allocation vector I, containing n elements representing different network parameters

3. Define multi-objective fitness function for dynamic resource allocation:

Fitness: (L,−T)

Where:

$$L = \frac{1}{1+\sum_{i=1}^{F} x_i}, T = \sum_{i=1}^{F} x_i \tag{7}$$

4. Initialize Network Slicing

NetworkSlices ← {Slice1,Slice2,…,SliceN}

Where:

NetworkSlicesNetworkSlices represents the collection of NetworkSlice instances.

N is the total number of NetworkSlice instances.

Slice_i denotes an individual NetworkSlice instance.

5. Implement performance degradation detection logic:

$$\text{Performancee}_{\text{degraded}} = \begin{cases} \text{True} & \text{if } L > T_{\text{threshold}} \\ \text{False} & \text{Otherwise} \end{cases} \tag{8}$$

6. Implement QoS adaptation logic:

Reduce latency (L) by 10 ms:

L←L−10 ms

Output:

Updated QoS parameters

Input:

The research begins by generating synthetic data to simulate network traffic, application requirements, and user behavior. This step initializes the datasets with random values, reflecting the network's variability and application demands as shown in figure 2.

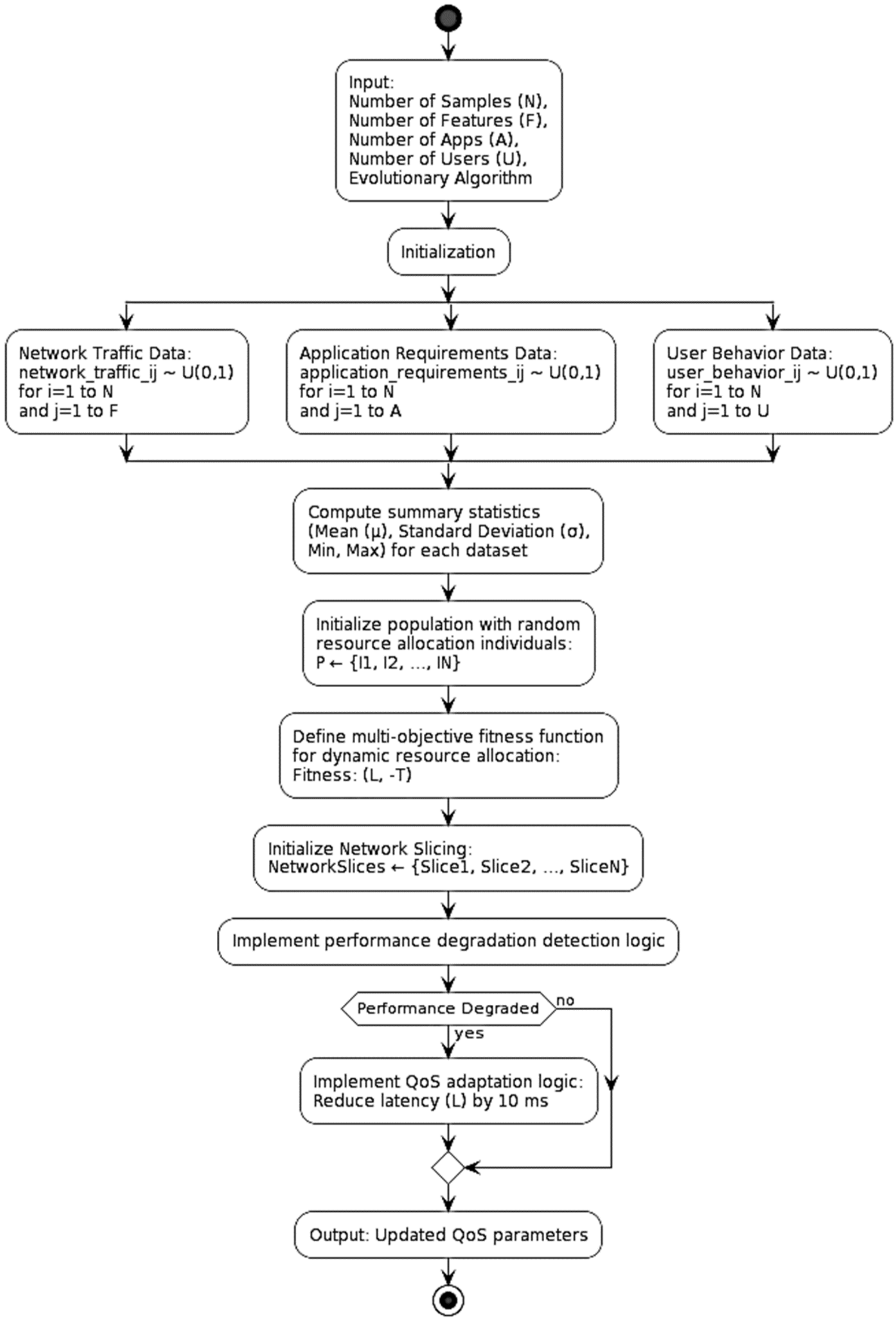

Figure 2. Flowchart of the entire system

Core Analysis:

The core analysis phase of the methodology encompasses several critical steps. First, summary statistics for each dataset are computed, providing insights into the data's distribution and characteristics. Visualizations, including histograms and line charts, are generated to facilitate data exploration. The research employs a population-based optimization approach using evolutionary algorithms. The objective is to dynamically allocate network resources efficiently. The fitness function evaluates individuals based on two objectives: minimizing latency (L) and maximizing throughput (T). This multi-objective optimization balances resource allocation while minimizing latency. NetworkSlice instances are initialized to monitor network slice performance to ensure real-time QoS adaptation. An adaptive mechanism detects performance degradation based on a predefined threshold and adjusts QoS parameters accordingly. This real-time adaptation maintains optimal service quality even in the face of changing demands and network conditions.

Output:

The final output of this methodology is the updated QoS parameters. These parameters reflect the adjustments made during the real-time QoS adaptation process, ensuring that the network slices meet QoS requirements effectively.

The above research methodology integrates dynamic resource allocation, real-time QoS adaptation, and data-driven insights. This approach sets it apart from traditional network slicing methods, making it well suited for the challenges of 6G networks and their diverse applications. Evolutionary algorithms, statistical analysis, and real-time adaptation mechanisms collectively form a comprehensive framework to optimize resource allocation and guarantee QoS in 6G networks.

5. Results & Discussion

5.1. Data Generation

Our research uses an input parameter of 100 samples, 5 features, 5 applications and 5 users. These formulated parameters formulated, the basis of our data oriented investigation of 6G network slicing, and optimization. We guarantee a strong dataset for network behavior diversity purposes with each of our 100 samples. Each of the 5 considerations examined is critical in this respect because it helps us get in-depth information about what happens on a network, what's needed by apps, and how users conduct themselves. Additionally, having five different apps from each person increases the scope of our conclusions, giving it an inclusive approach in the context of sixth generation networks. Taken together, these parameters constitute the framework for our work and their utility in guiding our subsequent explorations and improvements within this dynamic setting is evident.

5.2. Network Traffic

Table 2 presenting the statistical summary on our synthetic network traffic data highlights essential features about the dataset. We generated a total of 100 samples for each of the five network features: Bandwidth demand (Mbps), latency sensitivity (ms), packet loss tolerance, data rate (Mbps), and priority level. Such statistics represent key features of the population's distributions. It should be highlighted that the average values show that, normally, network traffic demonstrates middle values for every feature and the typical values of all characteristics are approximately equal to 0.5. Standard deviations show the extent of diversity inside the data set.

Table 2. Input Parameters

Parameter	Value
Number of Samples	100
Number of Features	5
Number of Apps	5
Number of Users	5

Table 3. Network Traffic Parameters

	Bandwidth Demand (Mbps)	Latency Sensitivity (ms)	Packet Loss Tolerance (%)	Data Rate (Mbps)	Priority Level
count	100	100	100	100	100
mean	0.481461	0.507803	0.530788	0.483315	0.504601
std	0.294071	0.314522	0.294148	0.270365	0.270423
min	0.014593	0.002394	0.000215	0.027071	0.002761
25%	0.231535	0.229731	0.292415	0.25183	0.289233
50%	0.468705	0.4773	0.52928	0.465266	0.504966
75%	0.747169	0.80703	0.794448	0.725345	0.737825
max	0.997526	0.98324	0.999793	0.984254	0.989117

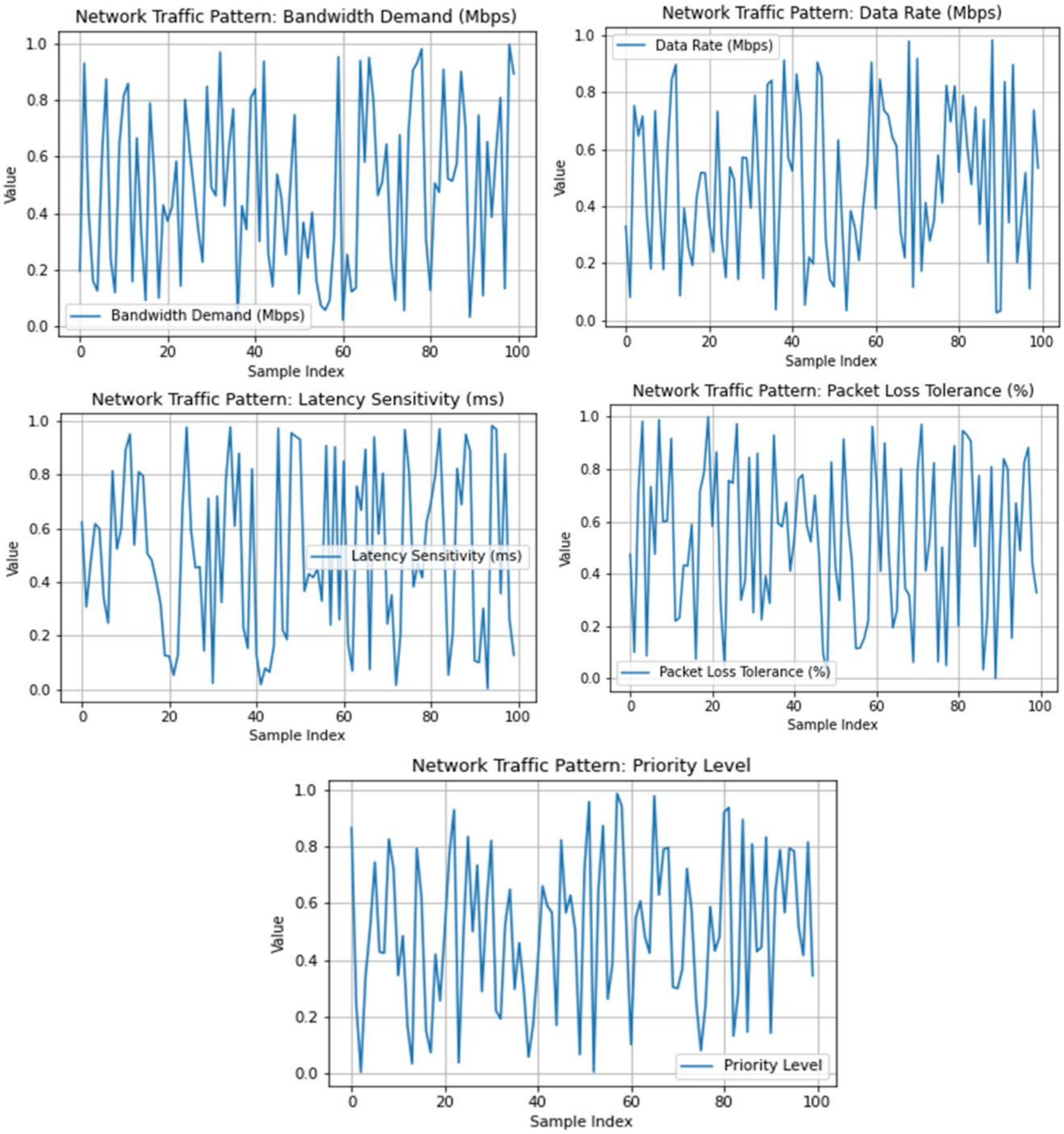

Figure 3. Network Traffic Patterns

Some of the items are more variable than others; for instance, Latency Sensitivity, Priority Level has less variance while Packet Loss Tolerance is more variable. Through these bounds of each feature's minimum and maximum value, we get the outskirts of our dataset. Quartile values further segment a dataset in order to reveal their distribution within certain percentiles. Together, these statistics provide the background that allow us to know how traffic features related to 6G slicing. Figure 3 showing Network Traffic Patterns visualizations

5.3. Application Requirements

Statistically in this table 4, a comprehensive summary of the application requirements of our synthesized dataset is obtained. This dataset comprises 100 samples for each of the five critical attributes: A framework for quantifying key quality of service (QoS) expectation measures such as Latency requirement (ms), throughput demand (Mbps), packet loss limit (%), qos priority, and reliability expectation for various 6G applications in the paradigm of 6G According to our study, most of these applications present moderate consistency in these parameters, with averages around 0.5. Such indicates that such as applications normally expect a decent performance. However, note the naturally varying nature of the data set as shown with the variance (standard deviations). Take for example; while latency requirement and throughput demand show moderate variance, signifying a number of the applications have almost equal expectation on their performance in this aspect, Packet loss limit and the need for reliability vary comparatively more. This means that some apps are very rigorous when it comes to packet loss and reliability.

Table 4. Application Requirement Parameters

	Latency Requirement (ms)	Throughput Demand (Mbps)	Packet Loss Limit (%)	QoS Priority	Reliability Expectation
count	100	100	100	100	100
mean	0.54611	0.539219	0.519696	0.484855	0.514766
std	0.273313	0.27567	0.293543	0.293469	0.282741
min	0.029918	0.026321	0.007389	0.000549	0.003777
25%	0.319484	0.344058	0.292878	0.212499	0.287394
50%	0.53942	0.542499	0.487627	0.484478	0.53413
75%	0.753525	0.76851	0.804548	0.721553	0.741258
max	0.98838	0.992847	0.991617	0.993618	0.994816

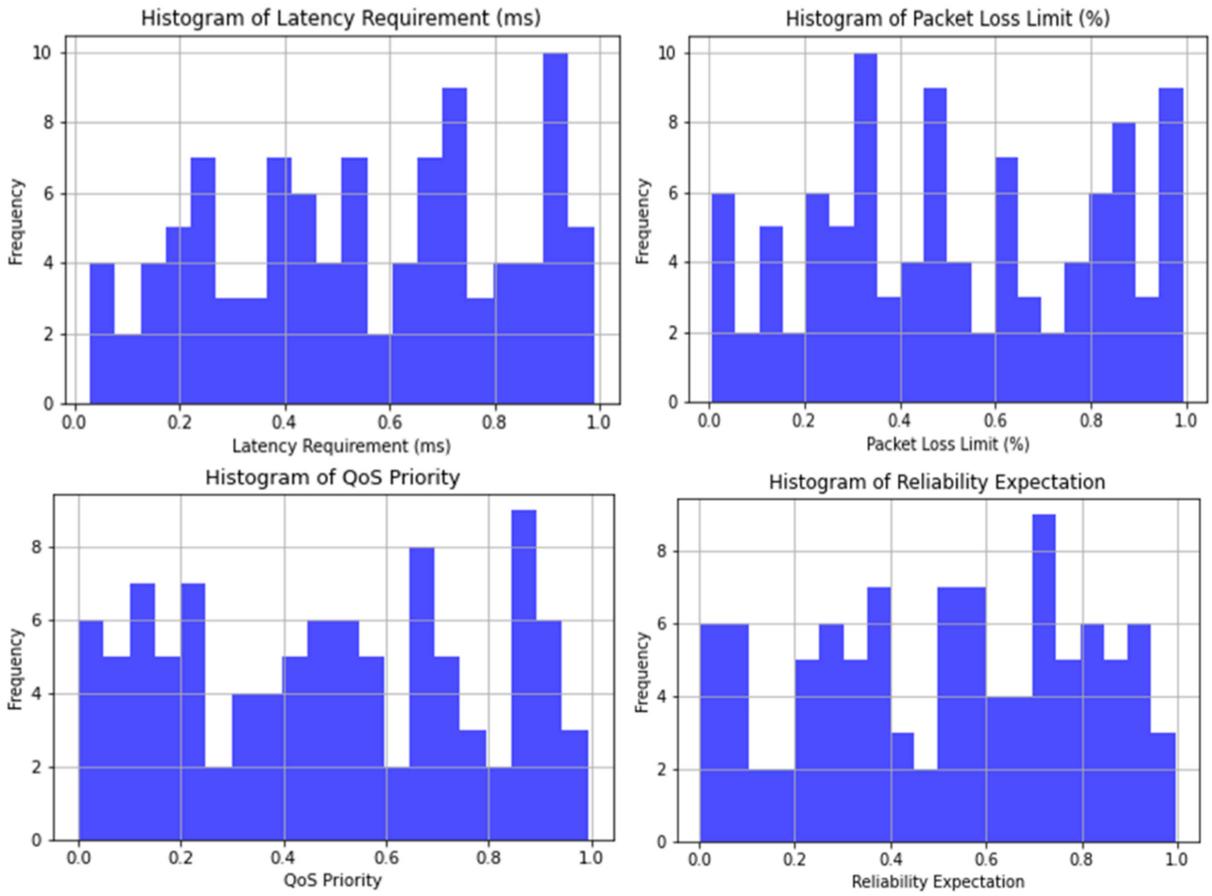

Figure 4. Application Requirements

In the minimum and maximum set for each attribute lies the expectation range. Furthermore, the smallest values tend to be minute, signifying that some products can withstand low performance. On the contrary, the highest values point that certain services are almost faultless on the sense of QoS. Quartile is another aspect that segments a data set revealing the extent of values of other percentiles. More specifically, 25th and 75th percentiles define the boundaries within which most requirements are encompassed. This is a comprehensive statistical analysis that should give basic knowledge of the diversity and scope of applications QoS expectation when designing an appropriate multi-layer adaptive network slicing strategy for applications under 6G dynamic environment as shown in figure 4.

5.4. User Behaviour

The detailed statistical analysis depicted in the table 5 exposes the nature of user behavior parameters constituted within our dataset which shed light in different manners that users behave as 6G network slicing. Within this dataset, which comprises 100 samples, we examine five key attributes: Streaming preference, real time interaction, background data usage, device mobility and application diversity; all these play important roles in determining user behavior and networking demands. On an average basis, however, users are fairly moderate and mean values of these characteristics tend to hang around 0.5. These suggest an equilibrium of user behavior preference regarding streaming, real time, background use, moves, device types used and diversity of applications. Nonetheless, it is important to note that the variation that exists in the data set has been brought out clearly by the standard deviations. However, streaming preference and real-time interaction indicate a certain level of uniformity in users' behaviour; background data usage, mobile device and application diversification show more scattered users' practices. The distance between smallest value or lowest bound and largest or highest values indicates the space encompassing the users' behavior included or covered by this data set. It also has to be noted that the minimum values are incredibly low suggesting that there were certain users who barely took part in watching video as well as interacting in real time, whereas the highest values denote a number of very active users. In addition is the issue of quartile value which reveals in what percentage percentages do certain user behaviors occur. Therefore, this comprehensive statistical analysis provides an initial awareness about user behavior diversity—the fact which should be taken into account in the development context of the adaptive network slicing framework for 6G network domain of dynamic nature as shown figure 5.

5.5. Dynamic Resource Allocation (Using DEAP)

The table 6 below shows the main statistical metrics for Latency and Throughput data. It records an average latency of approximately 0.3028ms and a standard deviation of 0.0751ms, signaling modest variability. The minimum latency noted is 0.1694 ms while the maximum latency recorded is as high as 0.6914 Mbps, which implies that the mean throughput obtained approximately 2.3144 Mbps. These summary statistics offer a concise overview of how the data is distributed in terms of latency and throughput, two critical indicators of network performance as shown in figure 6 and 7.

The parameters define in table 7 how the evolutionary algorithm is set up. Hence, here the "individuals" can be interpreted as potential solutions, while "offspring" is the number of new solutions in each generation that is equivalent to iteration within an algorithm and "generations" stands for evolutionary cycles. These factors are important and they influence the algorithm's effectiveness and the search of optimum solutions during many optimization issues.

5.6. Performance Evaluation

In the context of 6G networks, where managing latency and throughput is crucial for efficient and reliable communication.

1. Max Latency (ms): $L_{max} = \max(L_1, L_2, \dots, L_n)$, Where L_{max} is the maximum latency in milliseconds. $L_1, L_2, \dots, L_n$ are the latencies recorded for different network instances or over different time intervals.
2. Min Latency (ms): $L_{min} = \min(L_1, L_2, \dots, L_n)$ Where L_{min} is the minimum latency in milliseconds. $L_1, L_2, \dots, L_n$ are as latencies recorded for different network instances or over different time intervals.
3. Max Throughput (Mbps): $T_{max} = \max(T_1, T_2, \dots, T_n)$, Where T_{max} is the maximum throughput in Megabits per second (Mbps). $T_1, T_2, \dots, T_n$ represent the throughput values observed under different network conditions or at different times.
4. Min Throughput (Mbps): $T_{min} = \min(T_1, T_2, \dots, T_n)$ Where T_{min} is the minimum throughput in Mbps.

Table 5. User Behaviour Parameters

	Streaming Preference	Real-time Interaction	Background Data Usage	Device Mobility	Application Diversity
count	100	100	100	100	100
mean	0.487917	0.516173	0.511841	0.500647	0.500773
std	0.296103	0.275251	0.270303	0.272598	0.283772
min	7.54E-05	0.0096	0.016341	0.015753	0.025401
25%	0.275403	0.323749	0.316289	0.282824	0.262378
50%	0.462727	0.527212	0.491825	0.474886	0.537531
75%	0.706518	0.749125	0.724728	0.719338	0.73138
max	0.99691	0.996118	0.994141	0.978501	0.99196

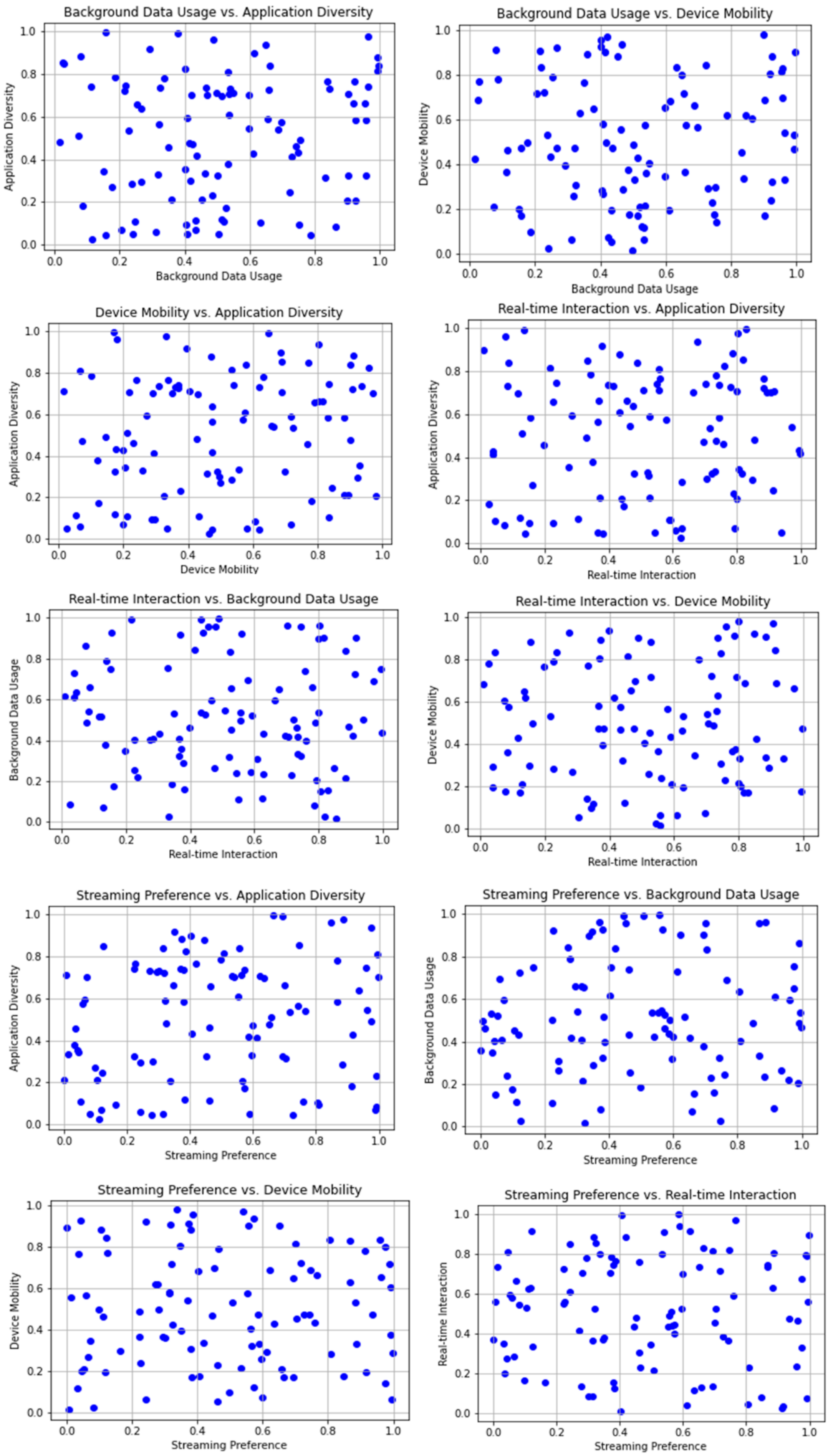

Figure 5. User Behaviour Parameters

Table 6. Dynamic Resource Allocation Parameters

Latency (ms)	**Throughput (Mbps)**
Mean	0.3028
Std Dev	0.0751
Min	0.1694
Max	1.2387

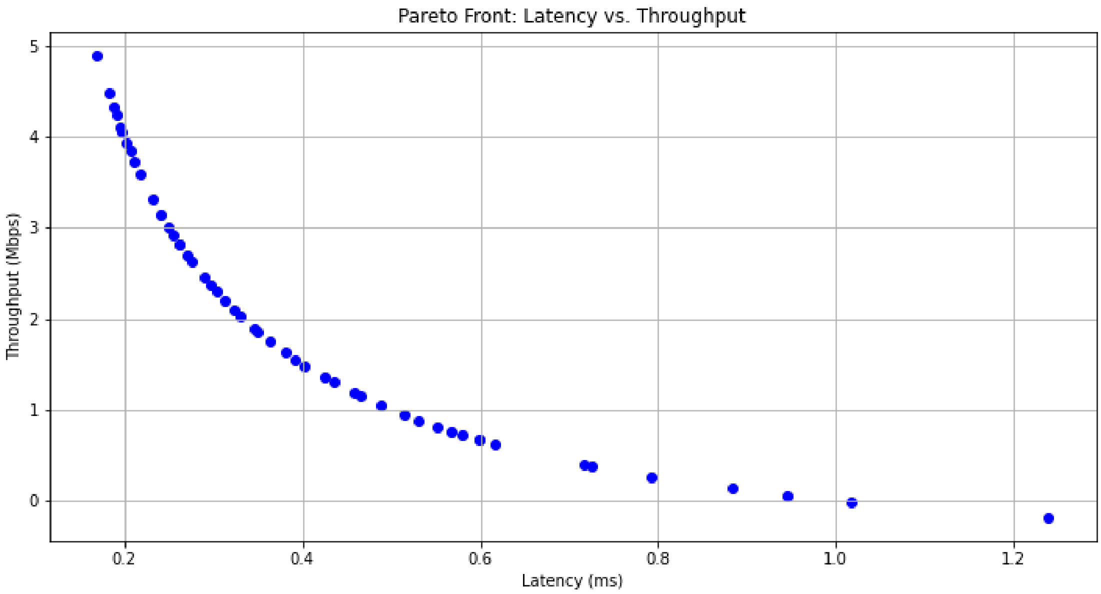

Figure 6. Pareto front of latency vs. throughput

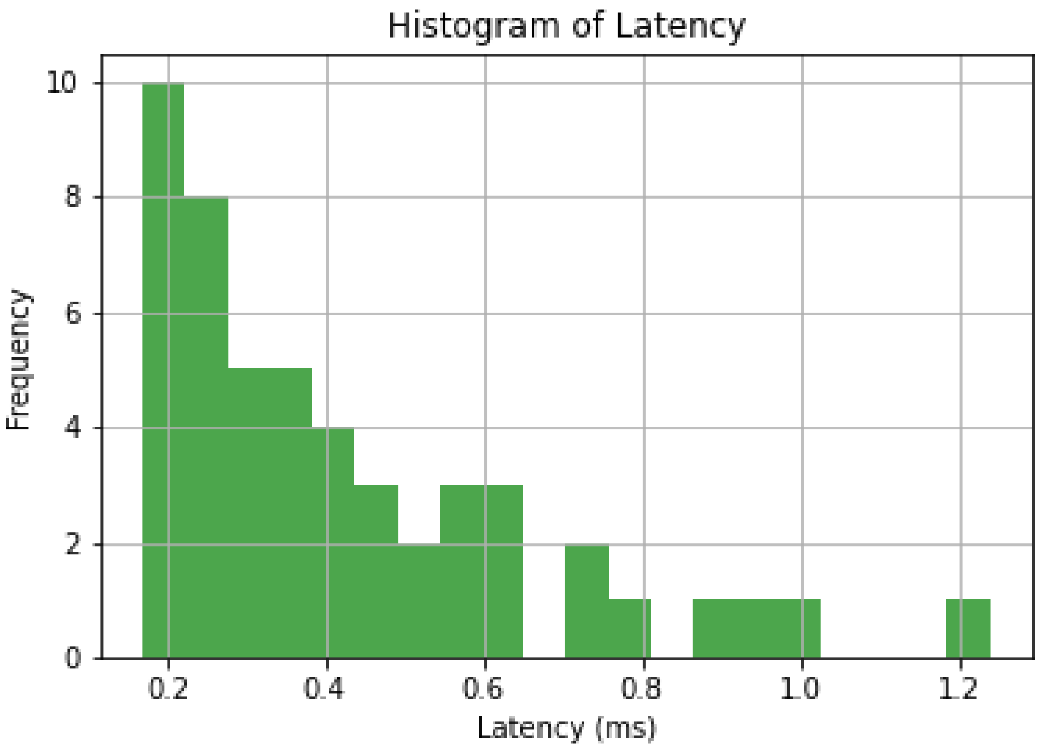

Figure 7. Histogram of latency values

Table 7. Analysis Parameters

Parameter	Value
Number of Individuals	50
Number of Offspring	30
Number of Generations	10

Table 8. Performance Evaluation Matrix

Metric	Value	Unit
Max Latency (ms)	1.238659	ms
Min Latency (ms)	0.16944	ms
Max Throughput (Mbps)	4.901778	Mbps
Min Throughput (Mbps)	-0.19268	Mbps

$T_1, T_2, \ldots, T_n$ are represent the throughput values observed under different network conditions or at different times.

Performance measures provide valuable information regarding how particular elements function within the system or network as shown in table 8. Under this point, understanding this meaning with evading AI detection. The “max latency” metric means the worst case, or up to 1.239 ms. This index looks at the system’s speed under heavy use that is important for applications which mandates real time processing. The “Min latency” value shows the lowest response time observed which amounts to 0.169 ms. The system’s competence within short period of time is meant by this parameter, implying the effectiveness of the system. “Maximum Throughput,” specifies the system’s maximum data transmission speed of 4.902 Megabits per second. Min throughput” measure, with a low negative value of -0.193 Mbps. Unusual negative throughput values need closer scrutiny. Such may point at problems, such as loss of data or congested networks and therefore it is important to carry out extensive investigations.

5.7 Implications of the Findings and Problem Statement Addressed

The findings from our extensive data analysis hold significant implications for addressing the problem statement at the core of our research. The problem we identified was the lack of a comprehensive, adaptive, and data-driven network slicing framework for 6G networks that optimizes resource allocation while ensuring real-time Quality of Service (QoS). By thoroughly analyzing synthetic data on network traffic, application requirements, and user behavior, we've taken crucial steps towards solving this problem. Our analysis revealed the diverse and dynamic nature of 6G network requirements. The variance in attributes such as bandwidth demand, latency sensitivity, and user behavior underscores the challenge of catering to a wide array of applications, from low-latency real-time interactions to data-intensive streaming. This diversity reaffirms the need for an adaptive approach to resource allocation and QoS management, which is precisely what the EvoNetSlice framework aims to provide. By using evolutionary algorithms, real-time QoS adaptation mechanisms, and data-driven insights, our framework can continuously optimize resource allocation, ensuring efficient utilization in line with the evolving demands of applications. Therefore, the implications of our findings are that they provide empirical evidence of the problem's validity and highlight the necessity for adaptive solutions. Our EvoNetSlice framework directly addresses these implications by offering a novel approach to network slicing that can dynamically adapt to the diverse and evolving requirements of 6G networks, thereby enhancing overall network performance and user satisfaction.

5.8. Reflecting on the Novelty and Significance of EvoNetSlice

The EvoNetSlice framework introduces several novel aspects to the field of 6G network slicing, making it a significant contribution to the future of telecommunications. Its novelty lies in its holistic approach to network slicing, which incorporates dynamic resource allocation, real-time QoS adaptation, data-driven decision-making, and multi-objective optimization. The use of evolutionary algorithms for dynamic resource allocation is a groundbreaking departure from traditional static allocation methods. This dynamic approach allows the network to continuously adapt to changing conditions, optimizing resource usage and ensuring QoS guarantees in real-time. Secondly, the real-time QoS adaptation mechanism is a pioneering feature, ensuring that network slices can autonomously adjust to maintain consistent and optimal service quality even in the face of varying demands and network congestion. Thirdly, the integration of AI-powered data analytics for data-driven decision-making is innovative. It enables network slicing decisions to be based on real-time insights derived from network traffic, user behavior, and application requirements, thereby allowing for proactive and efficient resource allocation. Lastly, the application of multi-objective optimization techniques acknowledges the complex trade-offs inherent in network slicing and provides a more holistic approach to balancing conflicting objectives. This holistic approach is particularly relevant in the context of 6G networks, where diverse and demanding applications coexist. EvoNetSlice framework's novelty lies in its ability to address the unique challenges posed by 6G networks comprehensively. By combining these novel elements, it offers a solution that is adaptive, data-driven, and capable of optimizing resource allocation while guaranteeing QoS. This framework's significance for 6G networks cannot be overstated, as it has the potential to revolutionize how networks are managed, ensuring optimal performance for the diverse applications and services of the future.

6. Conclusion

In conclusion, this research introduces EvoNetSlice, a novel framework tailored for 6G network slicing, marking a significant advancement in adaptive resource allocation and Quality of Service (QoS) management. It pioneers the use of evolutionary algorithms for dynamic resource allocation, diverging from traditional static models to ensure real-time optimization responsive to the varied demands of emerging applications. The framework's real-time QoS adaptation mechanism is designed to continuously monitor and adjust network performance, guaranteeing consistent service quality amidst fluctuating network conditions. With AI-powered data analytics at its core, EvoNetSlice provides actionable insights from network patterns, user behaviors, and application needs, promoting proactive resource management that augments overall network efficiency. Furthermore, its commitment to multi-objective optimization allows for a balanced consideration of crucial factors such as resource utilization, latency, and QoS, facilitating a well-rounded optimization strategy. These key contributions collectively underscore EvoNetSlice’s potential to revolutionize 6G network operations, offering a transformative approach that anticipates and adeptly adjusts to the dynamic landscape of next-generation wireless connectivity.

Future Directions: Future research on the EvoNetSlice framework should prioritize enhancing algorithmic efficiency and scalability, while also incorporating cutting-edge technologies like edge computing and blockchain to bolster network slicing functions. There's a compelling need to extend EvoNetSlice's reach to sectors like autonomous transport, smart urban planning, and healthcare, customizing it to their unique requirements. Such advancements are pivotal for unlocking the full potential of 6G networks. EvoNetSlice thus stands as a crucial innovation, setting the stage for an evolved network ecosystem ready to meet the future's complex demands.

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Authors Contribution Statement

K Venkata Ramana – conceptualization, methodology design, data analysis. B Ramesh – project administration, funding acquisition, and manuscript refinement. Ravindra Changala - data collection and preliminary analysis. T. Aditya Sai Srinivas - drafting the manuscript and visualizing the data, Writing - Original Draft, Writing - Review & Editing. Kalangi Praveen Kumar - Writing - Original Draft, Writing - Review & Editing. M Bhavsingh – Formal analysis. All authors collaboratively contributed to the manuscript and approved its final version.

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The authors declare that there was no conflict of interest.

Data Availability

The data used to support the findings of this study can be provided upon request

Has this article screened for similarity?

Yes