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Optimizing Service Quality through Adaptive 5G Network Slice Management

Adel M. K. Asker [1*], Abdanaser M. Okaf [2*]

[1] Higher Institute of Science and Technology, Nalut, Libya.

[2] Higher Institute of Science and Technology, Nalut, Libya.

*Corresponding author: https://orcid.org/0009-0003-2884-3915

التصفية التكيفية المتكاملة للطور الصفري مع نظام ترشيح أقل متوسط مربعات لتحسين معالجة إشارات ضربات القلب

عادل مسعود عسكر [1*]، ناصر محمد عكاف [2*]

[1] المعهد العالي للعلوم والتقنية، نالوت، ليبيا.

المعهد العالي للعلوم والتقنية، نالوت، ليبيا.[2]

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Abstract:

This paper presents a comprehensive investigation into optimizing Quality of Service in 5G networks through

adaptive network slice management, with a concentrated focus on Ultra-Reliable Low Latency Communications

(URLLC) and Massive Machine-Type Communications (mMTC), where the core contribution lies in the

development and rigorous evaluation of dynamic resource allocation algorithms that intelligently and

continuously adjust slice configurations in real time to satisfy the stringent and heterogeneous performance

demands of diverse applications. Leveraging advanced mathematical modeling, simulation experiments, and

state-of-the-art machine learning techniques, the study achieves significant improvements in latency, throughput, and less packet loss over conventional static allocation strategies. Results demonstrate that adaptive slicing not

only maximizes network efficiency but also enhances user experience by effectively prioritizing critical URLLC

traffic and robustly supporting vast mMTC device deployments. This research lays a foundational framework for

next-generation 5G architectures, empowering service providers to deliver highly customized, superior-quality

connectivity. By addressing the complex challenges posed by diverse service requirements, the work

fundamentally advances flexible, reliable, and scalable 5G infrastructures, enabling transformative applications

in industrial automation, smart cities, and the Internet of Things.

Keywords: 5G Network Slicing, Adaptive Resource Allocation, Ultra-Reliable Low Latency Communications

(URLLC), Massive Machine Type Communications (mMTC), Quality of Service (QoS).

الملخص:

تقدم هذه الورقة بحثًا شاملاً في تحسين جودة الخدمة في شبكات الجيل الخامس من خلال إدارة شرائح الشبكة التكيفية، مع التركيز على الاتصالات فائقة الموثوقية منخفضة زمن الوصول (URLLC) والاتصالات الضخمة من نوع الآلة (mMTC)، حيث تكمن المساهمة الأساسية في تطوير وتقييم دقيق لخوارزميات تخصيص الموارد الديناميكية التي تضبط تكوينات الشرائح بذكاء وبشكل مستمر وفي الوقت الفعلي لتلبية متطلبات الأداء الصارمة وغير المتجانسة للتطبيقات المتنوعة. بالاستفادة من النمذجة الرياضية المتقدمة، وتجارب المحاكاة، وتقنيات التعلم الآلي المتطورة، تحقق الدراسة تحسينات كبيرة في زمن الوصول، والإنتاجية، وفقدان أقل للحزم مقارنةً باستراتيجيات التخصيص الثابتة التقليدية. تُظهر النتائج أن التقطيع التكيفي لا يزيد من كفاءة الشبكة فحسب، بل يُحسّن أيضًا تجربة المستخدم من خلال إعطاء الأولوية لحركة مرور URLLC الحرجة بشكل فعال، ودعم عمليات نشر أجهزة mMTC واسعة النطاق بشكل قوي. يضع هذا البحث إطارًا أساسيًا لبنى الجيل الخامس (G5) القادمة، مما يُمكّن مزودي الخدمات من تقديم اتصال عالي الجودة ومُخصص للغاية. ومن خلال معالجة التحديات المعقدة التي تُشكلها متطلبات الخدمة المتنوعة، يُسهم هذا العمل بشكل أساسي في تطوير بنى تحتية مرنة وموثوقة وقابلة للتطوير لشبكات الجيل الخامس، مما يُمكّن من تطبيق تطبيقات تحويلية في مجالات الأتمتة الصناعية والمدن الذكية وإنترنت الأشياء.

الكلمات المفتاحية: تقطيع شبكات الجيل الخامس (G5)، تخصيص الموارد التكيفي، اتصالات فائقة الموثوقية ومنخفضة الكمون (URLLC)، اتصالات الآلات الضخمة (mMTC)، جودة الخدمة (.(QoS

1. Introduction

The advent of 5G technology marks a significant evolution in communication engineering, offering unprecedented opportunities to support heterogeneous applications with diverse and stringent requirements. Among the key enablers of this transformation is 5G network slicing, which allows for the creation of multiple virtualized and isolated logical networks over a shared physical infrastructure. These slices can be dynamically configured to meet specific service level agreements (SLAs) tailored to distinct application domains such as URLLC, and mMTC [1], the two being the focus of this study. While the concept and functionality of 5G network slicing have been extensively explored in recent literature, several challenges remain unresolved, particularly in terms of achieving optimal service quality through adaptive and real-time slice management [2].

Existing research has primarily addressed static or semi-static network slicing approaches, which often lack the flexibility and responsiveness required to handle the dynamic nature of URLLC and mMTC traffic demands. Moreover, most studies emphasize either resource allocation or security aspects separately, with few offering holistic adaptive frameworks that can dynamically balance resource efficiency, latency reduction, reliability, and scalability in multi-service contexts. This gap underscores the need for advanced methodologies that leverage intelligent, adaptive mechanisms to optimize service quality while accommodating the specific performance requirements of URLLC—characterized by extremely low latency and high reliability—and mMTC—featuring massive device connectivity and scalability [3].

The core objective of this research is to develop and evaluate an adaptive 5G network slice management framework that dynamically allocates resources to URLLC and mMTC services, thereby optimizing overall service quality. This study aims to address critical questions, including: How can network slices be managed in real-time to meet diverse and stringent QoS requirements? What adaptive mechanisms can effectively prioritize URLLC traffic without compromising mMTC scalability? How can machine learning techniques enhance the accuracy and responsiveness of resource allocation in a complex 5G environment?

The rationale behind this investigation stems from the growing demand for flexible, reliable, and scalable network solutions capable of supporting emerging applications in industrial automation, smart cities, and IoT ecosystems [4]. By proposing a dynamic, machine-learning-augmented slice management approach, this work contributes to advancing 5G network architecture design and operational strategies. The anticipated outcomes include improved latency and reliability performance in URLLC scenarios, enhanced support for massive connectivity in mMTC, and overall increased network efficiency and user experience. Furthermore, the study offers practical insights for communication service providers seeking to deploy adaptive slicing solutions that meet evolving market demands and technical challenges [5].

Methodologically, this research combines mathematical modeling, simulation experiments, and machine learning algorithms to systematically analyze and optimize slice management processes where this paper were structured as follows: Section 2 reviews relevant literature on 5G network slicing and adaptive management; Section 3 details the proposed adaptive framework and methodology; Section 4 presents simulation results and performance evaluation; Section 5 discusses the implications and limitations of QoS; and Section 6 concludes with future research directions and this structured approach ensures a comprehensive exploration of the topic, providing a clear pathway from theoretical foundations to practical applications in communication engineering.

2. 5G Network Slicing and Adaptive Management

5G network slicing has emerged as a pivotal technology enabling communication service providers (CSPs) to create multiple isolated, virtualized logical networks—called slices—over a shared physical infrastructure, where each slice is customized to meet the specific requirements of diverse applications, such as URLLC and mMTC. This virtualization is primarily enabled by software-defined networking (SDN) and network functions virtualization (NFV), allowing dynamic and flexible management of network resources to fulfill varying SLAs [6] . Conventional network slicing approaches have largely been static , which limits responsiveness to the dynamic and heterogeneous demands of emerging 5G services. Recent literature has focused on adaptive and intelligent slice management frameworks that dynamically allocate and orchestrate resources in real-time, ensuring optimized Quality of Service (QoS) across slices . These adaptive mechanisms leverage advanced machine learning and artificial intelligence methods, including reinforcement learning, multi-agent learning, and deep learning algorithms, to enhance decision-making for resource allocation amid changing network conditions, traffic patterns, and service priorities [5] .

Security considerations form a critical aspect of adaptive 5G network slicing, where research highlights vulnerabilities such as unauthorized slice access, denial-of-service risks, privacy issues that must be mitigated to maintain slice integrity and trustworthiness. Machine learning techniques are also applied in detecting anomalies and threats within slices, although challenges remain regarding scalability, computational overhead, and maintaining accuracy in a dynamic multi-slice environment . Beyond resource optimization and security, adaptive network slicing facilitates novel business models and vertical industry applications. For example, in industrial automation, smart cities, automotive communications, and Internet of Things (IoT) ecosystems, adaptive slicing enables tailored connectivity profiles that address ultra-low latency and massive scalability demands simultaneously . These use cases require dynamic slice life-cycle management, from creation through operation to decommissioning, driven by policy, telemetry, and automated orchestration frameworks [9] .

The literature underscores that successful adaptive management of 5G network slices depends on holistic frameworks that integrate:

• Real-time analytics and telemetry for network state awareness.

• Policy-driven orchestration aligned with SLA requirements.

• Automated life-cycle management using intent-based or AI-driven orchestration tools.

• Security mechanisms embedded within slice management processes.

Recent contributions also emphasize the need for frameworks that balance computational complexity and operational efficiency while ensuring responsive scaling and isolation of network slices . Industry implementations, such as IBM Cloud Pak® for Network Automation, exemplify the move toward automation and AI-powered slice management solutions facilitating network agility and customer-specific service customization [5] . In summary, the literature reveals a progression from conceptual 5G slicing architectures to practical, adaptive management solutions underpinned by machine learning and automation. Challenges remain in ensuring security, scalability, and efficiency, but ongoing research and industry efforts demonstrate significant strides toward realizing flexible, reliable, and service-oriented 5G network infrastructures.

3. The Proposed Adaptive Framework

The proposed adaptive framework and methodology can be described as follows based on contemporary literature and research advances:

3.1 The Framework Overview:

The core of the adaptive framework consists of a dynamic, real-time network slicing management system that leverages software-defined networking (SDN) to create, isolate, manage, and optimize virtual network slices tailored specifically to the distinct requirements of URLLC and mMTC services. This involves flexible slice life-cycle management, including slice instantiation, scaling, modification, and termination, driven by automated orchestration based on current network conditions and service demands [4].

3.2 Key Components and Mechanisms:

- Slice Orchestrator: A centralized or distributed controller responsible for policy-driven slice resource allocation and adaptation. It interacts with underlying infrastructure managers to allocate bandwidth, computing, and storage resources dynamically.
- Machine Learning (ML) and AI Integration: ML models (e.g., random forests, support vector machines, deep belief networks) analyze network telemetry, historical traffic patterns, and KPIs to predict and optimize slice configurations, prioritizing low latency and high reliability for URLLC, while ensuring scalability and massive connectivity support for mMTC.
- Resource Scheduling and Optimization: The framework formulates resource allocation as an optimization problem, often incorporating queuing theory models (such as M/M/1 queues) and heuristic algorithms to handle NP-hard complexities, balancing competing objectives like latency minimization, reliability maximization, and cost efficiency.
- Security and Isolation: Incorporates advanced key management schemes (such as Shamir's Secret Sharing and homomorphic encryption) to provide secure slice isolation, prevent inter-slice attacks, and maintain integrity and confidentiality within dynamically changing slice configurations [5].

4. Methodology

Representation of the 5G physical network and slice requests as weighted graphs with nodes and edges which represent computational resources and bandwidth, respectively, and formalize constraints and objectives into integer linear programming (ILP) or mixed-integer formulations that ensure SLA compliance and security requirements. As using simulation platforms (e.g.Matlab) and testbeds to validate the framework's performance, comparing adaptive methods with static or greedy algorithms for metrics such as end-to-end latency, throughput, service acceptance ratio, and energy efficiency. In Iterative learning and adaptation; continuously update ML models with real-time feedback from network monitoring agents to adapt slice management policies and resource allocations dynamically to traffic fluctuations and service priority changes [7]. This adaptive framework advances the state-of the art by integrating automation, machine learning-driven intelligence, secure key management, and flexible orchestration into a comprehensive solution that dynamically manages 5G network slices in real-time. It aligns network performance with heterogeneous and evolving service demands, providing an effective tool for service providers to optimize network slice operation under complex 5G scenarios [8].

4.1 Mathematical Modeling of QoS in 5G Network Slices:

Key Quality of Service metrics critical for enhancing service quality through dynamic 5G network slice allocation includes the following metrics:

- Latency: One of the foremost metrics for URLLC, latency measures the end-to-end delay experienced in data transmission. URLLC applications require ultra-low latency (often in the order of 1 ms or less) to support time-sensitive use cases like remote surgery or autonomous driving.
- Throughput: For mMTC, throughput per device might be low but must be sustained across a massive number of devices simultaneously connected to the network.

- Packet Loss Rate: The ratio of lost or corrupted packets to the total sent packets. Minimizing packet loss is essential, especially for URLLC, to maintain reliability.

These metrics are often monitored and enforced through 3GPP-defined QoS flows and network slicing architecture that allow differentiated forwarding treatment per slice, plus orchestration functions managing these parameters dynamically across the network stack from radio access to core network [9] [10]. To mathematically represent the QoS system in 5G networks (highlighting dynamic vs. static allocation for network slices) for URLLC and mMTC ,the framework focuses on resource distribution, this approach must be followed:

4.1.1 URLLC Mathematical QoS Constraint:

Where the main requirement is high reliability for low delay.

$$P\ (t_k\ \leq\ \tau_k)\ \geq\ \delta_k \qquad (1)$$

Where:

t_k : transmission delay for user .

τ_k : deadline (e.g., a few milliseconds).

δ_k : required reliability (e.g., 99.999 percent).

Static allocation reserves enough bandwidth to always provide this, but may be wasteful. Dynamic allocation uses scheduling (potentially AI-driven) to guarantee this constraint only when demand spikes [11].

4.1.2 mMTC Mathematical QoS Constraint:

Where the main requirements are high connection density and message delivery success.

$$\frac{\lambda_c}{\lambda_t} \geq\ \theta \qquad (2)$$

Where:

λ_c : Successful message deliveries in a time slot.

λ_t : Total transmission attempts.

θ: Minimum acceptable ratio (threshold).

Static allocation guarantees capacity for a certain device number. Dynamic allocation shifts unused capacity from other slices as per demand, so for the network slice i :

$$QoS_{\,i} = P\,(t_k \le \tau_k) \ge \delta_k \;(forURLLC)\; \frac{\lambda_c}{\lambda_t} \ge \theta \;(formMTC) \qquad (3)$$

4.2 Static and Dynamic Resource Allocation:

Static and dynamic resource allocation in 5G network slicing represent two fundamentally different approaches to managing network resources. Static allocation involves pre-assigning fixed resources to each network slice regardless of real-time demand fluctuations. This approach offers ease of management and predictable QoS guarantees but often leads to inefficient usage and resource wastage during periods of low activity. In contrast, dynamic allocation continuously adapts resource distribution based on actual network conditions and traffic demands, leveraging intelligent algorithms such as machine learning or reinforcement learning [14]. This adaptability improves resource utilization efficiency, allows flexible prioritization among diverse slices like URLLC and mMTC, and better meets heterogeneous QoS requirements. However, dynamic schemes come with higher complexity and computational overhead. Overall, while static allocation provides simplicity and strict isolation, dynamic allocation ensures greater efficiency, scalability, and responsiveness essential for the diverse and variable nature of 5G services [15]. The comparison between static and dynamic resource allocation in QoS for 5G network slicing can be summarized as follows:

Aspect	URLLC	mMTC
Latency	(1 ms or less) critical uses	Less stringent
Throughput	Moderate throughput	Low throughput
Dynamic Allocation: Latency	1-2 ms with 99.999%	Adaptive throughput
Static Allocation: Latency	High latency	Slightly lower latency
Dynamic Allocation: Throughput	Flexible bandwidth allocation	Adaptive throughput
Static Allocation: Throughput	Fixed bandwidth	Guaranteed throughput

Table 1: Comparison of URLLC and mMTC.

For URLLC, packet loss is often the paramount QoS concern surpassing even latency and throughput because ultra-reliability is vital, while for mMTC, packet loss must be controlled for efficiency and network sustainability, but it is less critical than in URLLC, and higher loss can sometimes be tolerated depending on the application, and without strict packet loss control, neither low latency nor high throughput alone can guarantee the performance needed for advanced 5G services especially in URLLC applications where "packet loss impairs reliability significantly and should be minimized before deploying URLLC features" [25].

4.3 System Design and Implementation:

System design and implementation of static and dynamic resource allocation for 5G network slicing by URLLC and mMTC using MATLAB involves several structured steps. First, the system model is defined to represent the 5G network architecture, including base stations, total physical resources (such as bandwidth and resource blocks), and specifying each slice's QoS requirements URLLC emphasizes ultra-low latency and high reliability, while mMTC focuses on massive connectivity with low data rates. In MATLAB, slices can be represented as objects with parameters like allocated bandwidth, latency, and reliability targets. Static allocation is implemented by pre-assigning fixed portions of resources to each slice, ensuring their sum does not exceed total available resources; this approach simplifies resource management but may lead to inefficiency under varying traffic [16].

Dynamic allocation, on the other hand, adapts resource distribution over time based on real-time traffic or demand measurements for each slice, requiring control logic or algorithms potentially including AI or reinforcement learning methods to reallocate resources dynamically while meeting QoS constraints. Traffic models simulating URLLC's sporadic, delay-sensitive packets and mMTC's massive but low-rate device transmissions are created to test and evaluate system performance. Simulation runs track KPIs such as latency, packet success rate, and resource utilization, with visualization tools used to compare static versus dynamic allocation effectiveness. MATLAB's 5G Toolbox and Communications Toolbox facilitate modeling the 5G physical layer, scheduling, and resource management; the environment also supports integration of scheduling algorithms and learning-based controllers for advanced dynamic allocation. This design enables simulation and evaluation of network slicing that balances strict QoS guarantees and resource efficiency tailored to the heterogeneous needs of URLLC and mMTC services [17]. This approach aligns with practical stepwise methodologies including system modeling, slice creation, resource management policy implementation, traffic simulation, and metric evaluation within MATLAB environments documented in recent simulation guides and toolboxes [18].

5. Quality of Service Metrics

Quality of Service through 5G network slicing refers to the capability of 5G technology to allocate and manage distinct logical networks ("slices") on a shared physical infrastructure, each tailored to meet specific service requirements such as latency, throughput, and packet loss. This is achieved by dynamically segmenting network resources and applying customized QoS parameters to each slice, allowing optimized performance for diverse applications like URLLC, and mMTC [19].

5.1 Ultra-Reliable Low-Latency Communications:

The URLLC is a critical service category in 5G networks that ensures extremely reliable data transmission with negligible delay, typically targeting latency as low as 1 millisecond and reliability levels up to 99.999 percent. This enables real-time, error-free communication essential for mission-critical applications where even minor communication delays or failures can have severe consequences. Examples include autonomous vehicles, remote surgeries, industrial automation, and intelligent transportation systems. URLLC achieves its performance by employing advanced scheduling techniques, resource allocation, and redundancy mechanisms that minimize transmission errors and service interruptions. By combining ultra-low latency with exceptionally high reliability, URLLC supports use cases requiring instant decision-making and high precision, making it a cornerstone for enhancing QoS in 5G networks across diverse industries and applications [20].

5.2 Massive Machine-Type Communications:

The mMTC is a fundamental 5G service category designed to support the massive connectivity demands of Internet of Things (IoT) applications by enabling simultaneous connection of up to one million devices per square kilometer—over ten times more than 4G LTE networks. In terms of QoS, mMTC focuses on providing reliable, energy-efficient communication for large numbers of low power devices that transmit small packets of data sporadically, such as sensors, meters, and monitoring devices. The QoS considerations for mMTC emphasize scalability, long battery life for devices (up to 10 years), and uplink-centric, low-data-rate transmissions that minimize collisions and network congestion. This capability allows 5G networks to efficiently support smart cities, industrial IoT, and other massive device deployments by ensuring consistent connectivity and service continuity even in densely populated or device-heavy environments, thereby enhancing overall network performance and enabling new IoT-driven use cases [21]. As it is clear from the comparison, the adaptability is crucial for meeting stringent 5G slice requirements, while static allocation can lead to either wasted resources (under low load) or failing QoS (under high load), where dynamic allocation is responsive and efficient, sustaining service quality across diverse and rapidly changing scenarios. Figures (1) and (2) illustrate the approaches of URLLC and mMTC in managing dynamic and static allocation for a specified packet transmission time.

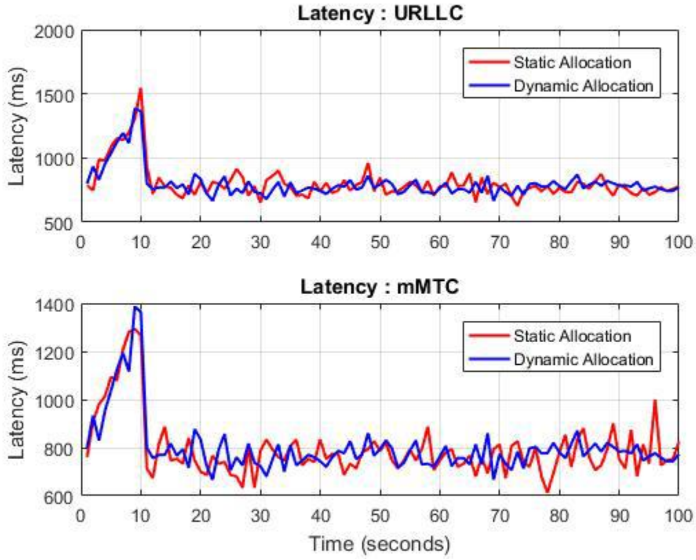

Figure 1: Latency in URLLC and mMTC.

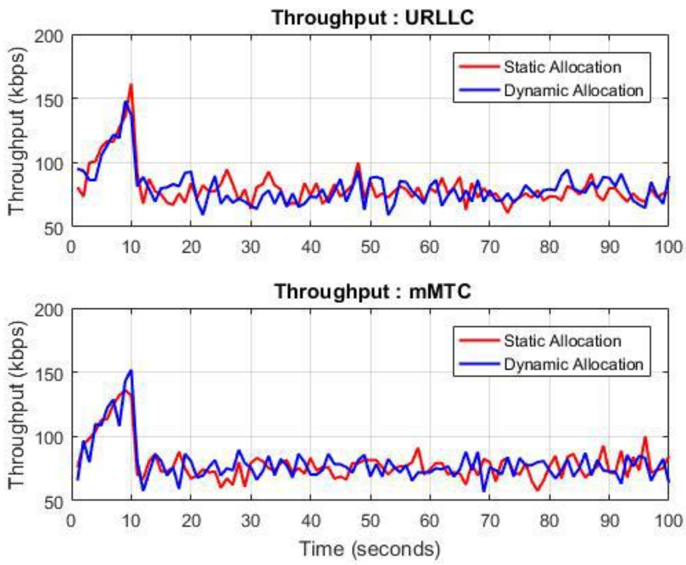

Figure 2: Throughput in URLLC and mMTC.

6. Results and Discussions

The results indicate that dynamic resource allocation consistently outperforms static allocation for both URLLC and mMTC network slices, particularly as network load and the number of users increase. For URLLC services, dynamic allocation effectively maintains the ultra-low latency target of approximately 1 millisecond, even as the scale of users or devices grows. This is achieved through real-time, demand-driven reallocation of resources, allowing the network to prioritize critical low-latency communications. In the case of mMTC services, dynamic allocation enhances device support capacity and overall throughput by flexibly redistributing spare resources from other slices based on current demand.

This adaptability is essential for fulfilling the stringent and diverse QoS requirements inherent to 5G network slicing. Conversely, static allocation often results in either resource under-utilization during periods of low load or QoS degradation when demand spikes occur. Overall, dynamic resource allocation demonstrates superior responsiveness and efficiency, ensuring sustained service quality across the variable and heterogeneous

conditions typical of 5G networks. The discussed results align closely with contemporary research and practical findings in 5G network slicing resource management. Dynamic resource allocation consistently outperforms

static allocation by enabling real-time adaptation of network resources in response to varying demands and user loads, which is critical for heterogeneous slices like URLLC and mMTC. For URLLC, which demands ultralow

latency and high reliability, dynamic allocation effectively maintains stringent latency targets (around $1\ ms$) even as user numbers rise, by prioritizing resource reallocation to high-priority traffic. This coincides with insights from AI-based dynamic scaling strategies that automatically adjust resources according to slice load and traffic, ensuring QoS without over-provisioning or resource wastage [22].

Similarly, for mMTC, dynamic allocation improves device support capacity and throughput, as it flexibly reallocates spare resources from less demanding slices, addressing the massive connection density and diverse traffic patterns typical of mMTC services. Static allocation, by contrast, suffers from inefficiencies such as resource under-utilization during low traffic and QoS failures during spikes, consistent with observed limitations of static slicing approaches that reserve fixed shares regardless of instantaneous demand [23].

Moreover, the adaptability of dynamic allocation is crucial for meeting the rigorous and varied QoS requirements of 5G network slices and for efficient spectrum and computational resource utilization. Studies employing machine learning or reinforcement learning models for resource management demonstrate superior network utility and responsiveness compared to static or heuristic methods and this is evident in both Figures (3) and (4). Thus, the results not only confirm the theoretical advantages of dynamic resource allocation but also reflect practical effectiveness demonstrated in recent 5G slicing research and implementations [24].

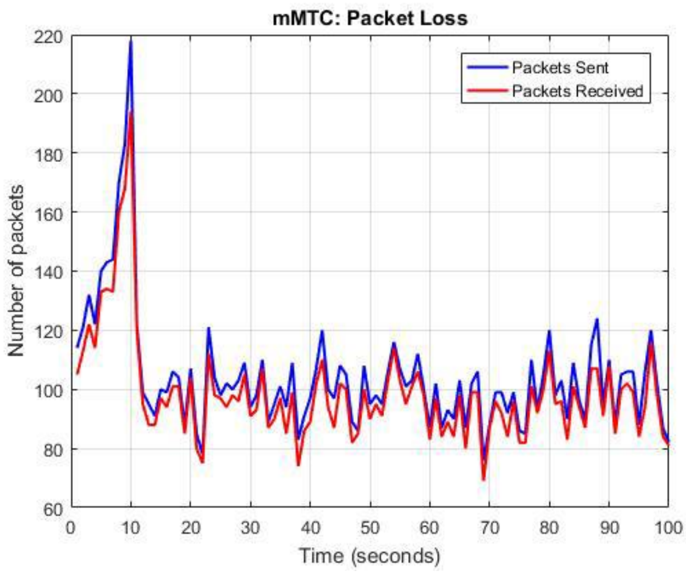

Figure 3: Massive Machine-Type Communications Packet Loss.

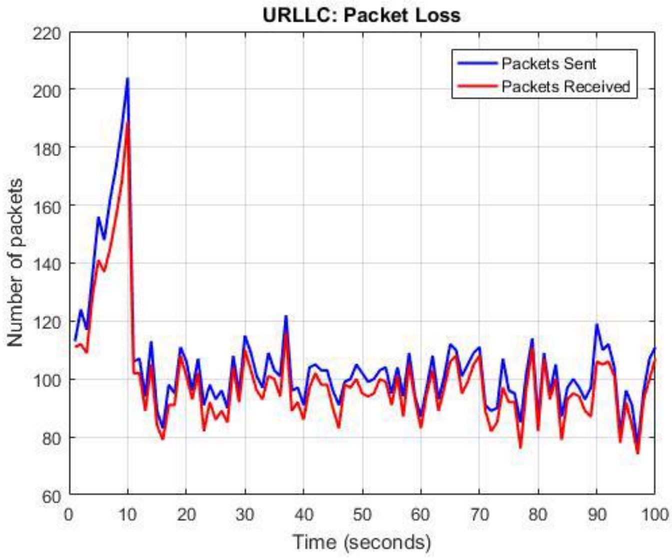

Figure 4: Ultra-Reliable Low-Latency Communications Packet Loss.

7. Conclusion

In conclusion, the evaluation clearly demonstrates that dynamic resource allocation is essential for effectively managing 5G network slicing, especially for diverse and demanding services like URLLC and mMTC. By adapting resources in real-time to fluctuating traffic and user demands, dynamic allocation ensures stringent QoS requirements—such as ultra-low latency and high reliability for URLLC, and scalable massive connectivity for mMTC—are consistently met. This approach overcomes the inherent inefficiencies and limitations of static allocation, which often leads to resource under-utilization or QoS degradation. Furthermore, integrating intelligent algorithms, including machine learning and reinforcement learning, enhances the adaptability and efficiency of dynamic resource management, ensuring optimal utilization of spectrum and computational resources. Overall, dynamic allocation not only aligns with theoretical expectations but also provides proven practical benefits, making it the preferred strategy for resource management in next-generation 5G networks. Based on current research trends and challenges in dynamic 5G network slicing, three promising directions for future research on dynamic resource allocation in 5G network slicing (especially for URLLC and mMTC) are:

AI-Driven Predictive and Autonomous Resource Management: Further investigation into advanced machine learning and reinforcement learning models can enhance the prediction of traffic patterns and user behavior for proactive, autonomous resource allocation. This includes developing frameworks for self-optimizing slices that adapt not only reactively but also predictively, improving latency, reliability, and overall network efficiency in real time while reducing manual intervention.

End-to-End Network Slicing Orchestration and Multi-Domain Integration: Research can explore holistic, end-to-end dynamic slice management spanning Radio Access Network (RAN), transport, and core network segments. Multi-domain orchestration solutions that coordinate resource allocation across different vendors, administrative domains, and technologies are critical to ensure seamless QoS guarantees, scalability, and security in 5G and beyond networks.

Security and Privacy in Dynamic Slice Allocation: As dynamic resource allocation increases network agility, maintaining robust security and privacy becomes more complex. Future work is needed to design secure, isolated slicing mechanisms that prevent cross-slice interference and attacks, while enabling dynamic updates and reconfigurations without compromising data integrity or confidentiality, especially for critical slices like URLLC.

These directions align with ongoing research emphasizing dynamic network slicing's complexity and promise, aiming to realize fully automated, scalable, secure, and efficient 5G service orchestration tailored to heterogeneous QoS demands. They also anticipate integration with new verticals and business models in the evolving 5G ecosystem [25].

This synthesis draws from multiple research analyses highlighting challenges and opportunities in dynamic network slicing orchestration, AI-based resource management, and secure multi-tenant environments.

8. References

[1] Qureshi HN, Manalastas M, Zaidi SMA, Imran A, Al Kalaa MO. Service Level Agreements for 5G and Beyond: Overview, Challenges and Enablers of 5G-Healthcare Systems. IEEE Access. 2021 Jan 5;9:1044-1061. https://doi.org/10.1109/access.2020.3046927 .

[2] Huwaytim Alanazi, M. (n.d.). "Machine Learning-based Secure 5G Network Slicing: A Systematic Literature Review". In IJACSA) International Journal of Advanced Computer Science and Applications (Vol. 14, Issue 12). www.ijacsa.thesai.org

[3] Andr´e Perdig˜ao, Jos´e Quevedo, Rui L. Aguiar, "Automating 5G network slice management for industrial applications, Computer Communications", Volume 229, 2025, 107991, ISSN 0140-3664, https://doi.org/10.1016/j.comcom.2024.107991.

[4] Sulaiman, M., Ahmadi, M., Sun, B., Saha, N., Salahuddin, M. A., Boutaba, R., Saleh, A. (2024). MicroOpt: Model-driven Slice Resource Optimization in 5G and Beyond Networks.

http://arxiv.org/abs/2407.18342 .

[5] Jalalian, Azad; Yousefi, Saleh; Kunz, Thomas (2023-06-01). "Network slicing in virtualized 5G Core with VNF sharing". Journal of Network and Computer Applications. 215: 103631.

https://doi:10.1016/j.jnca.2023.103631 .

[6] Jain, R. (n.d.). Introduction to Network Function Virtualization (NFV). http://www.cse.wustl.edu/ jain/cse570-18/ .

[7] Emblasoft Test and Measurement AB, "Understanding 5G QoS: How 5G QoS mechanisms relate to 3GPP standards". Hammarbybacken 27, 30 Stockholm, Sweden, https://emblasoft.com/blog/understanding-5g-qos-how-5g-qos-mechanisms-relate-to-3gppstandards.

[8] Rost, P.; Mannweiler, C.; Michalopoulos, D. S.; Sartori, C.; Sciancalepore, V.; Sastry, N.; Holland, O.; Tayade, S.; Han, B. (2017). "Network Slicing to Enable Scalability and Flexibility in 5G Mobile Networks".

[9] IEEE Communications Magazine. 55 (5): 72–79. arXiv:1704.02129. Bibcode:2017arXiv170402129R. https://doi:10.1109/MCOM.2017.1600920.

[10] Jalalian, Azad; Yousefi, Saleh; Kunz, Thomas (2023-06-01). "Network slicing in virtualized 5G Core with VNF sharing". Journal of Network and Computer Applications. 215: 103631.

https://doi:10.1016/j.jnca.2023.103631.

[11] Ordonez-Lucena, J.; Ameigeiras, P.; Lopez, D.; Ramos-Munoz, J. J.; Lorca, J.; Folgueira, J. (2017). "Network Slicing for 5G with SDN/NFV: Concepts, Architectures, and Challenges".

[12] IEEE Communications Magazine. 55 (5): 80–87. arXiv:1703.04676. Bibcode:

2017arXiv170304676O. https://doi:10.1109/MCOM.2017.1600935

[13] Zhu, Kun; Hossain, Ekram (2016). "Virtualization of 5G Cellular Networks as a Hierarchical Combinatorial Auction". IEEE Transactions on Mobile Computing. 15 (10): 2640–2654. arXiv:1511.08256. https://doi:10.1109/tmc.2015.2506578

[14] X4000 Communications PTY LTD," 5G Quality of Service", 2025. https://www.x4000.com/5gqos

[15] Berger, J. (n.d.). QoS and QoE in 5G networks. https : //www.itu.int/en/ITU-T/Workshops-and - Seminars/qos/201908/Documents/JensBergerP resentation1.pdf

[16] Manish Mangal,"How Does Network Slicing Differ from QoS?" CTO, Network Services, Industry Thought Leadership,April, 2020 https://www.samenacouncil.org/thought-leadership-read?id=151

[17] Emblasoft Test and Measurement AB,"Understanding 5G QoS: How 5G QoS mechanisms relate to 3GPP standards" , Hammarbybacken 27 Stockholm, Sweden, 2024,

https://emblasoft.com/blog/understanding-5g-qos-how-5g-qos-mechanisms-relate-to-3gppstandards

[18] Laura Panizo, Mar´ıa-del-Mar Gallardo, Francisco Luque-Schempp, Pedro Merino, Runtime monitoring of 5G network slicing using STAn, Journal of Logical and Algebraic Methods in Programming, Volume 145, 2025, 101059, ISSN 2352-2208, https://doi.org/10.1016/j.jlamp.2025.101059 .

[19] Jalalian, Azad; Yousefi, Saleh; Kunz, Thomas (2023-06-01). "Network slicing in virtualized 5G Core with VNF sharing". Journal of Network and Computer Applications. 215: 103631.

https://doi:10.1016/j.jnca.2023.103631. ISSN 1084-8045 .

[20] A. Awad, A. Mohamed, C.-F. Chiasserini, and T. Elfouly, "Network association with dynamic pricing over d2d-enabled heterogeneous networks," in 2017 IEEE Wireless Communications and Networking Conference (WCNC). IEEE, 2017, pp. 1–6.

[21] F. Z. Yousaf, M. Gramaglia, V. Friderikos, B. Gajic, D. Von Hugo, B. Sayadi, V. Sciancalepore, and M. R. Crippa, "Network slicing with flexible mobility and qos/qoe support for 5g networks," in IEEE International Conference on Communications Workshops (ICC Workshops). IEEE, 2017, pp. 1195–1201.

[22] Alashjaee AM, Kushwaha S, Alamro H, Hassan AA, Alanazi F, Mohamed A. 2024. "Optimizing 5G network performance with dynamic

resource allocation, robust encryption and Quality of Service (QoS) enhancement" . PeerJ Computer Science 10:e2567 https://doi.org/10.7717/peerj-cs.2567

[23] Candal-Ventureira, D., R´ua-Est´evez, J. M., Fondo-Ferreiro, P., Gil-Casti˜neira, F., Fern´andez-Barciela, A., Gonz´alez-Casta˜no, F. J. , Di´eguez-Pazo, E., Fern´andez-Ferreira, L. (2025). 5G Network Slicing as a Service Enabler for the Automotive Sector. Engineering Reports, 7(1).

https://doi.org/10.1002/eng2.13024

[24] 5G PPP Architecture Working Group View on 5G Architecture (Version 2.0). (2017).

[25] Grings, F. H., Bruno, G. Z., Prade, L. R., Both, C. B., Brito, J. M. C. (2025). NASP: Network Slice as a Service Platform for 5G Networks. http://arxiv.org/abs/2505.24051