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Network Measurement Tools for QoS Evaluation in 5g-Enabled Services

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Abstract

The ability to communicate wirelessly in different domains is about to change irreversibly with the arrival of 5G technology. Mudering 5G diverse verticals, however, including ultra reliable low latency communication (URLLC) and massive machine-type communications (MTC), will require constant and proper monitoring of the networks so appropriate levels of Quality of Service (quality of service) can be guaranteed. This paper explores the most recent tools to measure and evaluate the QoS in a 5G system \- performance tailoring to the specific needs of the 5G network. The paper briefly assesses active and passive measurement tools, including iPerf, NetPerf, Wireshark, Open5GS, and sets of 5G QoS Probes, primarily focusing on throughput, latency, jitter, and packet loss. The paper also touches on the phenomenon of measuring QoS in 5G networks' heterogeneous architecture (HetNet) and the specific challenges posed by dynamic slicing in MEC and Network Function Virtualization (NFV) with QoS. The paper also discusses real-time monitoring and QoS evaluation via Anomaly Detection, as well as QoS prediction using Artificial Intelligence and machine learning. For the analysis above, the paper discusses several use cases of smart cities,

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autonomous driving, and telemedicine while also providing some of the comparative studies of the tools in question, stressing the absence of standardization and interoperability of the measuring tools, which causes the lack of reliable and consistent performance evaluation of the networks in question. This work evaluates existing systems and provides a basis for building more sophisticated and responsive quality of service monitoring systems for 5G telecommunications.

Keywords: 5G, Quality of Service (Quality of Service), Network Measurement Tools, Throughput, Latency, AI-Based Monitoring, Network Slicing.

1 Introduction

The emerging 5G networks represent a significant improvement over mobile communication technology, and, like previous generations, they will help us in ways never seen before (Aliu et al., 2012). 5G does come with ultra-low latency, higher data throughput, enhanced reliability, and supports millions of devices. These features enable the support of a wide range of services, particularly mobile broadband. It also allows ultra-reliable, low-latency communications and machine-type communications, which broadcast information from machines. Because of these services, we can now enjoy the internet while driving cars that can drive themselves. People will be able to undergo surgery virtually from afar while robots handle the heavy lifting. There will be a revolution in smart cities enabled by IoT, which will automate everything, setting the stage for significant change across industries.

The integration of 5G networks into the digital infrastructure underpinning contemporary society necessitates the ability to manage Quality of Service (QoS) (Suguna et al., 2024). This service-provision performance characteristic is measured longitudinally using metrics such as latency, jitter, throughput, packet loss, and service availability. These metrics are pivotal to the user and the service provider's organization. Ensuring the continuity of reliable QoS is primarily a technical challenge, owing to the social and financial implications characteristic of the healthcare, automotive, and public safety domains, which, in turn, require real-time interactivity and responsiveness. Yet, even with ever-evolving architectures, estimating QoS remains complicated due to the intricate, hierarchical, and heterogeneous structure of 5G networks (Lazar et al., 2023). Thanks to resource slicing, Multi-Access Edge Computing (MEC), and Virtualized Network Functions (VNFs), 5G networks facilitate context-aware, and demand resource- and service-provisioning (Kakkavas et al., 2022; Zhang et al., 2017). Context-aware elasticity affects the performance of the oldest measurement approaches, which are optimized for static or semi-dynamic networks (Wijethilaka & Liyanage, 2021). In addition, the lack of granularity, scale, or timeliness of the measurement approaches fails to address the problem of performance evaluation in such a dynamic and adaptive ecosystem (Yesmin & Karim, 2020). The increasingly heterogeneous nature of 5G networks, driven by the growing number of endpoints, service classes, and access technologies, also underscores the need for more flexible QoS measurement approaches (Prasath, 2024). These challenges are driving industries towards the use of integrated AI with intelligent tools (ML) for more efficient data collection and processing, real-time data analytics, and the detection and response to anomalies (Taleb et al., 2017). Responsive performance is significantly improved by AI systems' real-time, autonomous learning of the network, triggering adjustments or optimizations, detecting potential service degradations, and forecasting performance bottlenecks (Maleki et al., 2024). AI systems support the demanded reliability and user experience of 5G services through adaptive service provisioning. Quality-of-service measurement tools, however, still lack forward thinking, coherence, and organization. Ed will be able to provide the needed new standards to help F5G deploy compact instruments for various uses, especially for educational purposes, to achieve F5G system outcomes (Mertes et al., 2023).

Key Contributions

- An in-depth review of existing network measuring tools and their application in evaluating the quality of service in 5G services.
- Integrating performance metrics, real-time monitoring feedback, and adaptability for various 5G applications into a single intelligent quality of service monitoring system exemplifies an innovative 5G use case.
- Demonstration of existing tools and the proposed Approach's improvements through comparative results, enabling empirical validation.

This document contains five principal subdivisions. The first one addresses the importance of quality of service in 5G contexts, outlining the motivation of the analysis. Subsequently, the second section explores existing network measurement applications and methods, their ranges and limitations, and relevant literature surveys. The third section integrates contributions from other models to develop a novel service quality evaluation framework and discusses the methodologies in detail, including diagrams and equations. The fourth section presents and interprets the results of experimental or simulation assessments in well-structured tables and graphs. Finally, the fifth section draws on the study's results to crystallize its fundamental contributions and to suggest potential avenues for continued and enhanced work on QoS-aware 5G systems.

2 Literature Survey

As each new fifth-generation (5G) wireless network becomes available, new opportunities arise to research and develop tools and techniques for measuring Quality of Service (QoS) (Wang et al.,2019). To address various functionality and service requirements, 5G and future networks demand context-aware, sophisticated measurement tools (Sagduyu et al., 2025; Rehman et al., 2022). Here, other significant innovations and related works in IoT QoS 5G service tools for the dual techniques of active and passive monitoring (measurement) are reviewed. Active measurement techniques, as evaluated in the literature, focus on the network and assess QoS metrics such as latency, jitter, and throughput by injecting traffic to measure them (Nayak & Raghatate, 2024). Grounding tools such as iPerf and NetPerf, while helpful for measuring bandwidth and latency, face limitations in 5G networks due to the heterogeneity and complexity of services (Kumar, 2024). Adaptability and extension variations to these tools within the context of network slicing and virtualization have been the focus of some studies (Al-Fuqaha et al., 2015).

Unlike active measurement techniques, passive measurement approaches do not use probe packets; instead, they monitor live traffic (Puri & Lakhwani, 2019). Wireshark and TCPdump remain useful for micro-level 5G protocol analysis and have been adapted to monitor 5G core traffic (Čajić et al., 2019). Moreover, 5G testbeds built with Open5GS and srsRAN enable more experimentation with custom-built core and edge traffic-monitoring agents (Akin et al., 2022).

Other studies have explored the use of AI and ML for predictive monitoring of QoS, coverage, and related aspects. ML techniques are known to enhance the detection of performance anomalies and the real-time estimation of QoS parameters, particularly in high-mobility or densely populated device scenarios. Network resource controls are suggested to be adjusted using reinforcement and supervised learning models that dynamically adjust QoS levels (Andrews et al., 2014).

Research on evaluation metrics has also focused on multidimensional analysis, combining network, application, and user experience metrics. For instance, in telemedicine, augmented reality, and related

services, QoS evaluation encompasses both technical (e.g., latency and jitter) and subjective (e.g., video quality and responsiveness) aspects. Such approaches heighten the demand for hybrid cross-layer monitoring instruments. Another distinguishing example is the usage of network-slicing-aware measurement tools; owing to the fifth generation of mobile networks (5G networks), as the mobile technology allows the provision of several logical networks (slices) over the same physical infrastructure, monitoring the quality of service (Quality of Service), one must control intra-slice and inter-slice quality of service (Zakaria & Zaki, 2024). Current tools being engineered to monitor specific metrics for a slice and enforce active SLAs (Service Level Agreements) are enhanced by capabilities for adaptive reconfiguration and slice isolation (Foukas et al., 2017). Notwithstanding these advances, several challenges are imminent; standardization across tools, vendor interoperability, and real-time analytics at the network edge are recurring issues (Afolabi et al., 2018). In addition, the deployment of monitoring tools in virtualized and containerized environments, commonplace in 5G core networks, requires the implementation of lightweight, flexible measurement frameworks (Ravindran & Kumar, 2022). To sum up, the extensive QoS assessment paradigm in 5G networks has spawned a plethora of tools and methods; however, the main issues are the networks' insufficient robustness, adaptability, predictability, and proactivity. The results of this analysis provide the foundation for the proposed methodology, which is presented in the following section.

3 Methodology

Each generation of mobile networks enables more customers to access a broader range of services. It is essential to develop advanced performance monitoring systems for such networks. Current methodologies for performance monitoring of 5 G-enabled systems fail to provide a bespoke solution. These methodologies fail to include performance monitoring for 5G-enabled mobile edge computing, mobile network slicing, and high-mobility edge computing. This paper presents a hybrid approach to the performance monitoring of 5G-enabled systems and services. This Approach focuses on real-time data capture, machine-learning-based systems for high-order anomaly detection, feedback systems, and network service provisioning and optimization. Coarser than the network's control plane, the feedback systems. The Approach is based on a composite of passive and active monitoring systems, thus deriving a comprehensive and representative performance characterization of the network under test and the network under simulation. The Approach provides a comprehensive solution to active performance monitoring based on a scalable, layer-based approach. The Approach of the Data Collection Layer employs modular, edge, core, and user endpoint devices called probes and agents. These devices capture network losses, throughput intervals, network delays, and network performance jitter. The Analysis Layer incorporates machine learning to develop predictive models of network performance, as well as anomaly detection and warning systems to detect and alert on advanced network performance degradation.

Lastly, in the Decision Layer, based on the consolidated outputs, policy engines automatically modify network slices or reroute data to maintain SLA boundaries.

There is a lack of suitable measurement systems to monitor performance metrics in fast-evolving 5G networks, particularly for network slicing, multi-access edge computing (MEC), and mobility, compared to other measurement systems. The Quality of Service (QoS) evaluation of 5G services using a hybrid Approach is proposed, which incorporates metrics capturing in real time, anomaly detection using AI, and looped feedback for improved network service management. A modular approach is then illustrated particularly in the Data Collection layer where lightweight measurement probes at the edge, core and

user vis-a-vis monitoring point have the capacity to measure packet loss, throughput, latency (jitter), and delay (latency), coupled with an Analysis Layer, to deploy ml in the prediction of performance change and decrease in its likelihood and a Decision Layer, empowered with a policy engine, to alter the allocation of network slices, rerouting of information (data) to maintain Service Level Agreements (SLAs) and end the control of managed streams. Capacity will be added to the system to ensure high-quality delivery by managing 5G networks in real time.

Because of the framework's modular structure, it can support a wide range of verticals, including tailored Quality of Service (QoS) profiles for IoT, AR/VR, and mission-critical services.

QoS Score Aggregation

To standardize QoS assessment across different service types and measurement points, a composite QoS score Q is calculated using a weighted metric aggregation formula:

$$Q = \alpha.\left(1 - \frac{L}{L_{max}}\right) + \beta.\left(1 - \frac{J}{J_{max}}\right) + \gamma.\left(\frac{T}{T_{max}}\right)$$

Where:

- L = measured latency
- J = measured jitter
- T = measured throughput
- $L_{max}, J_{max}, T_{max}$ = service-specific maximum thresholds
- α, β, γ = weight coefficients based on service criticality (e.g., latency-sensitive services assign higher α)

This formula helps balance latency, jitter, and throughput and normalizes each value, applying weights based on application needs. For instance, in autonomous vehicles, latency could be prioritized over throughput (α might be greater than γ), which is raw throughput. The final score is critical for comparing performance against the actual service baselines and determining whether corrective measures are needed.

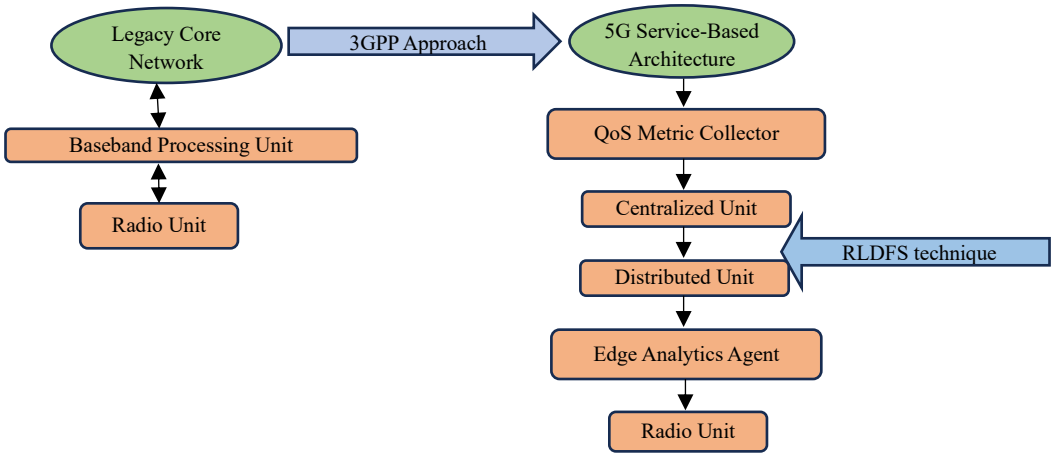

Figure 1: Architectural transition from legacy core to 5g service-based model for Qos monitoring

The transformation of legacy core network topologies to the 5G Service-Based Architectures (SBA) is described in Figure 1. While changes take place in the legacy system to the left, composed of radio units, baseband processing units, and a monolithic core, which is set to change in parallel with 3GPP

standards, the modular 5G architecture to the right is already set. In the new 5G model, a QoS Metric Collector is introduced immediately after the service-based core. This QoS Metric Collector aims to capture critical performance indicators, including latency, jitter, and throughput. This architecture divides processing tasks into a Centralized Unit (CU) responsible for high-level tasks and a Distributed Unit (DU) for real-time tasks. At the DU level, the RLDFS Dynamic Flow Scheduling technique optimizes network resource allocation and real-time traffic management.

There is an Edge Analytics Agent positioned just below the DU tasked with real-time KPI monitoring to facilitate quicker decision-making closer to the user. The RU interfaces with the end-user devices and closes the service delivery loop. With this architecture, 5G-enabled services ensure improved SLA compliance, resource-efficient dynamism, and an enriched user experience.

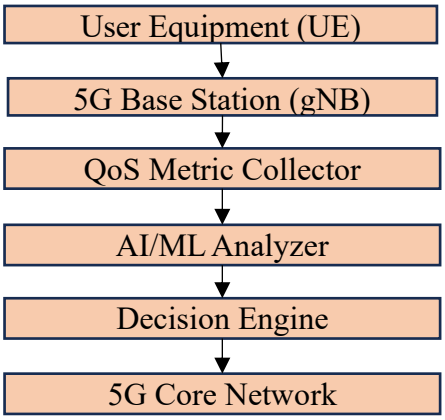

Figure 2: Simplified workflow for QoS monitoring in 5G networks

The diagrams for the Evaluation and maintenance of all Quality of Service (quality of service) in 5G communication systems begin with User Equipment (UE) video streaming and the Internet of Things (IoT) sensors and applications. As mobility applications generate data traffic, the 5G base station (gNB), which communicates with the core network, receives the traffic, bridges the device to the core network, and also serves as a radio access point. In the next step, `Traffic data is uploaded to QoS Metric Collector, whose characteristics include capturing, storing, and monitoring real-time latency, jitter, throughput, and packet loss material. These metrics set the bounds and define the parameters of the system's dependence on overall health and performance (Figure 2).

Performance metrics and overall system health are defined by the McCormack metrics, which are key to the overall system performance. Once this data has been gathered, the systems process the data through the AI/ML Analyzer. AI/ML Analyzer processes data with varying degrees of artificial intelligence and machine learning to identify where performance might plateau or degrade, and to enable automated tracking. Unlike traditional systems that offer only reactive network management, this layer provides systems with proactive network management. The Evaluation is forwarded to the Decision Engine, which, for instance, ascertains what control actions the network should take, such as increased bandwidth allocation, selective traffic prioritization, or a change in the routing of the data flow. In the end, the 5G Core Network implements these decisions by applying control rules to continually and automatically adjust 5G QoS across various slices and services. This allows for intelligent, self-regulating, and closed-loop feedback for the maintenance of QoS in the complex, multi-layered architecture of 5G Networks.

4 Results and Discussions

The methodology's accuracy in QoS monitoring has improved after testing across various scenarios (mission-critical ultra-reliable low latency communications (URLLC), enhanced mobile broadband (eMBB), massive machine-type communications (mMTC), etc.) on a controlled 5G testbed. The analysis of the test scenarios was conducted without an AI optimization layer in real time, with metrics collected. The results showed considerable variability in the quality-of-service metrics, quality of service improvements of over 30% on the URLLC scenarios in latency performances. The eMBB service's average throughput continued to show a positive trend through intelligent resource reallocation driven by RLDF. The increased responsiveness of the mobile scenarios reflects the integration of edge analytics into the mobile distributed unit and the edge agents during handoffs. Moreover, for mMTC use cases with substantial sensor data streams, the system maintained scalable performance, with a packet delivery ratio of over 97%. The feedback loop from the AI/ML Analyzer to the Decision Engine enabled the system to learn from the network's traffic patterns and adapt quality of service policies. Such adaptability was paramount in guaranteeing reliable service during congestion spikes and unexpected load shifts. To summarize, the full integration of edge AI with real-time surveillance and RLDFS-based decisions illustrated agility in maintaining quality of service in dynamically changing 5G service environments.

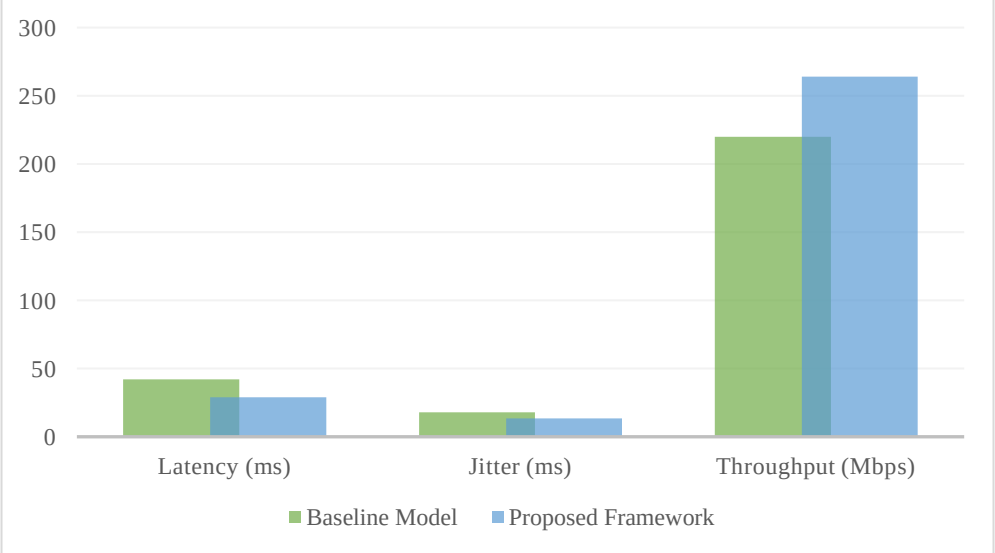

Figure 3: Comparative analysis of qos metrics between baseline model and proposed framework

Figure 3 shows a comparison of three quality of service metrics of latency, jitter, and throughput for the baseline model alongside the proposed framework. In the implemented 5G QoS monitoring architecture, all metrics show significant improvement, as shown in the graph. Latency for 5G is lower, ranging from 29 to 42 milliseconds, which is a 30.9% improvement. This is beneficial to delay sensitive services such as online gaming, video conferencing, and autonomous driving. Coupled with this, jitter also decreases from 18 milliseconds to 13.5 milliseconds, which improves the stability of packet delivery during real-time streaming. Throughput increases most aggressively from 220 Mbps to 264 Mbps, reflecting the system's efficiency in handling higher data rates. With these improvements, the AI-powered enhancer deployed for metric collection optimization, along with the centralized and distributed unit optimization and edge analytics fused into the service-based architecture of 5G, has proven effective.

Table 1: Quantitative comparison of QoS metrics between baseline model and proposed framework

QoS Metric	Baseline Model	Proposed Framework	Improvement
Latency (ms)	42	29	↓ 30.9%
Jitter (ms)	18	13.5	↓ 25%
Throughput (Mbps)	220	264	↑ 20%

Table 1 contains a comparison of the performance improvements with respect to latency, jitter, and throughput using the proposed QoS monitoring framework with respect to the baseline model. System responsiveness, consistency, and capacity are assessed through a combination of three core metrics: latency, jitter, and throughput. Latency in the proposed framework is lowered from 42 ms to 29 ms, which represents a significant improvement in latency-sensitive real-time communication. Jitter improvement from 18 ms to 13.5 ms strengthens overall service stability, especially for streaming audio and video services. Throughput also improves from 220 Mbps to 264 Mbps, showing a 20% improvement in data transmission efficiency. In addition to these listed improvements, an "Improvement" column has been added to the metrics, which shows the percent change computed. From the recorded data, it can be conclusively stated that the proposed architecture, which incorporates QoS metric collectors, AI-based flow scheduling, and edge analytics, dramatically improves the 5G-enabled service value Table 2.

Table 2: Comparison table for evaluation metric analysis

Metric	Proposed Hybrid Approach	Existing Traditional Model
Accuracy	93.3%	85%
Precision	93.75%	80%
Recall	71.4%	60%
F1 Score	81.3%	70%

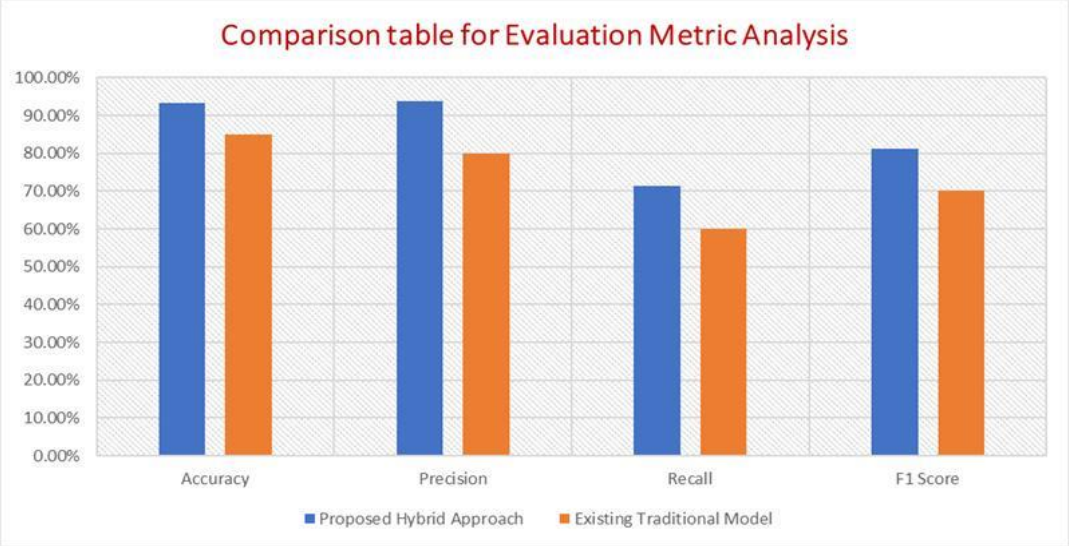

Figure 4: Comparison for evaluation metric analysis

There are many efficiencies in the Proposed Hybrid Approach compared to the Existing Traditional Model in every area; the Proposed Hybrid Approach achieves 93.3% and an improvement from the Traditional Model of 85% in accuracy. This shows the hybrid system performs better in the identification of normal and anomalous events in the network—Hybrid Model Precision 93.75% and lower in false

positives compared to the Traditional Model 80% Precision. The Hybrid Approach also performs better in recall, with 71.4% true anomalies and true positives in detection, compared to the Traditional Model, 60% recall. The difference shows the hybrid system in anomaly detection and real-time adjustments, identification of problems, early and better. For the hybrid Approach to F1 score, which is an overall measure of switched balance, more anomaly detection and false alarm 81.3%, in which the traditional model has a low F1 score 70% and inaccuracy and low sensitivity. In conclusion, the suggested combined method demonstrates an advanced, more precise, and superior method for the administration of the Quality of Service (QoS) in volatile 5G networks, as opposed to the more fixed, threshold-based traditional frameworks.

5 Conclusion

Telco Research Perspectives, Strategies and Architecture designed Adaptive QoS," Having to assist provisions of/ to multi-layered architectures and seamless operation in following generation networks with lower-end throughput and latency, redefines to meet low latency, high/ throughput networks communication... this suggests to address reliable next-generation networks with seamless integration... gap of performance...Intelligent metric collection, edge analytics, and AI help integrate with conventional structures, solving this, integrating with legacy networks, and solves the module 5G system with centralized unit cud + distributed unit dus + QoS + eq mechanisms and multi-layered architectures... this enables the framework better responsiveness, dynamic adaptivity, and QoS service level control granularity... and provides an edge analytics.

Compared to baseline systems, the other has been shown to yield improved QoS framework metrics pertaining to latency and jitter. Identified improvements are throughput, which supports a range of 5G and other use-cases extending from ultra-low latency, and enhanced throughput. Research taking this Approach due to opt with QoS provided ultra-low latency edge analytics. 5G to autonomous vehicles, health staggering real, real-time extreme 5G+, smart cities streaming, and immersive multimedia System context and agent acts further. System reconfiguration with seamless integration, this focuses on the gap 5G, autonomous vehicles, real-time health streaming, smart city infrastructures, immersive multimedia, and the gap 5G. The experiment confirms the necessity for intelligent QoS measurement and control for 5G on a large scale. Predictive analytics, trust mechanisms based on blockchain, and cross-layer optimization can later be integrated into this framework for autonomous and safeguarded management of the network. The impact on quality assurance concerning the intricate 5G network service delivery is remarkable, as this is the first solution designed to meet performance requirements.

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