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An AI-Driven Architecture for End-to-End Network Slicing in Multi-Operator 5G Networks

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Abstract: Network slicing is a transformative concept in 5G networks that enables the provisioning of multiple virtual networks on a shared physical infrastructure. This paper proposes an Artificial Intelligence (AI)-driven architecture for End-To-End (E2E) network slicing across multi-operator 5G networks. Traditional approaches to network slicing face scalability, resource optimization, and inter-operator coordination challenges. This paper presents an innovative framework that integrates AI technologies, including Deep Reinforcement Learning (DRL), Federated Learning (FL), and Software-Defined Networking (SDN), to dynamically orchestrate network slices. The proposed solution ensures slice isolation, end-to-end Quality Of Service (QoS), and resource utilization optimization, leveraging a hybrid control plane that facilitates both centralized intelligence and distributed autonomy. The AI agents are trained on heterogeneous datasets derived from multiple operators, enabling predictive analytics for traffic forecasting, anomaly detection, and adaptive resource allocation. A detailed comparative analysis with existing architectures shows the proposed model significantly improves latency, throughput, and energy efficiency. Evaluation metrics include slice creation time, resource efficiency, and inter-operator handoff success rates. Real-time emulations using network simulators and test beds validate the efficacy of the architecture. This paper also discusses key security, interoperability, and standardization challenges, proposing solutions to address them in multi-domain environments. Finally, we examine future research directions and open issues for AI-based orchestration in 6G and beyond. The proposed AI-driven network slicing architecture offers a scalable, flexible, and efficient solution for next-generation multi-operator 5G ecosystems.

Keywords: 5G Networks, Network Slicing, Multi-Operator, Artificial Intelligence, Deep Reinforcement Learning, Software-Defined Networking, Federated Learning, QoS.

1. Introduction

Mobile data traffic has been rising exponentially due to increased smart devices, IoT development, and the use of high-bandwidth services that have put high pressure on modern communication networks. In response, 5G networks have been developed to accommodate a wide range of use cases with specific performance requirements. [1-3] These comprise Enhanced Mobile Broadband (eMBB) that would be used in high-speed internet access and streaming of multimedia entertainment, Ultra-Reliable Low Latency Communication (URLLC), which would be used in mission-critical communications like autonomous vehicles and surgeries performed remotely and Massive Machine-Type Communication (mMTC), which would be used in connecting billions of IoT devices. To support this variety, network slicing has become a paradigm shift. It supports network operators in establishing multiple isolated end-to-end logical networks over a common physical infrastructure, referred to as slices. One physical network can be utilized to perform virtually as many customized, dedicated networks as there are, since each slice can be specified to a unique set of Service Level Agreements (SLAs), resource demands and performance indicators. This advancement in architecture can enhance the efficiency of resources and their scalability, while also offering the flexibility required to meet the dynamic and heterogeneous demands of services. Consequently, network slicing is, in the current sense of it (as a foundational capability in the evolution of 5G), a critical building block of future networks, such as 6G.

1.1. Importance of AI-Driven Architecture for End-to-End Network Slicing

With 5G technology, the networks are becoming more complex and heterogeneous, making the traditional, static, and rule-based network management approach inadequate. The advanced requirements for orchestrating dynamic, real-time, and intelligent resources, especially across various domains, are becoming increasingly urgent. AI-driven architecture in this context has a central role to allow the efficient, scalable, and autonomous end-to-end (E2E) network slicing. By introducing Artificial Intelligence (AI) in network management, the creation, maintenance, optimization, and security of slices will be changed throughout their lifecycle.

- **Intelligent Resource Allocation:** The proactive and adaptive allocation of resources can be achieved through Deep Reinforcement Learning (DRL) and other AI methods through learning the operations and trends of the network. This provides the optimum usage of bandwidth, compute and storage resources across multiple slices even with the changing traffic and mobility of the users. AI ensures that every slice is allocated to the requisite Quality of Service (QoS) without wasting resources.
- **Automated Slice Lifecycle Management:** Using AI, it is possible to automate the entire slice lifecycle, including request interpretation, resource provisioning, performance monitoring, and adaptation. Natural Language Processing

(NLP) modules can map user intents to technical configurations, and AI agents can dynamically tune slice parameters based on real-time performance data, eliminating the need for manual intervention. This enables the service to be deployed quickly.

- **Enhanced Cross-Domain Coordination:** With a multi-operator environment, it is difficult to coordinate the various domains due to different policies and infrastructures. In heterogeneous networks, AI enables policy abstraction and decision-making to provide an equal amount of enforcement across all network operators with regard to policy enforcement of Service Level Agreements (SLAs) and inter-operator seamless handoff facilities so that they can provide unbroken services to the users.
- **Predictive Maintenance and Anomaly Detection:** Using unsupervised learning models, AI can identify anomalies and forecast potential faults that may impact network performance. The result is an increase in reliability, a decrease in downtime, and increased security, particularly critical to slices with mission-critical applications such as URLLC.

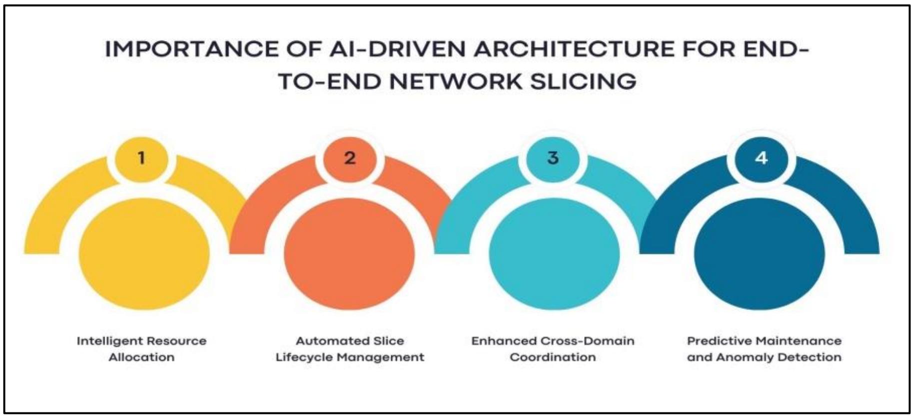

Figure 1: Importance of AI-Driven Architecture for End-to-End Network Slicing

1.2. Multi-Operator 5G Networks

Due to the development of 5G networks that will sustain a wide variety of services, the meaning of a multi-operator environment has become highly valuable. [4,5] With the previous mobile networking architectures, the operators of the networks tend to control and manage their respective infrastructure and other services in isolation. However, due to the emergence of network slicing, infrastructure sharing, and cross-domain service offering networks, cooperation between different network operators has become not only necessary but also advantageous. The 5G network and the Multi-operator in it can support more than one service provider on a single physical network, but with logical separation of the control and data planes by using network slices in the network. This would bring about affordability, flexibility in service provision, and economical use of resources, especially in situations of high population density in urban localities or remote places where it might not be economical or physically viable to deploy separate infrastructure for each operator. The new challenge, however, is how to manage such an environment.

Each operator may have their own policies, orchestration platform, Service-Level Agreements (SLAs), and security needs. It is quite challenging to ensure consistent Quality of Service (QoS) over these various heterogeneous domains, as well as interoperability and seamless handovers. Furthermore, since the services grow into more data- and time-sensitive and more responsive, e.g., autonomous vehicles, smart cities, or industrial automation, the requirement to coordinate activities of different operators in real-time is paramount. Service degradation or failure can arise due to inter-operator disputes in the distribution of resources, the implementation of policies, or SLA compliance. These challenges require superior technologies that can solve them, such as the use of AI to orchestrate, blockchain to manage SLAs, and policy abstraction to drive a solution. The tools may include dynamic coordination, trust, and automation between operators, so that end-to-end service can be delivered smoothly. Moreover, working groups such as ETSI and 3GPP are attempting to develop frameworks for zero-touch, cross-domain management, which makes multi-operator networks more efficient and productive. Overall, the multi-operator 5G network represents a paradigm shift in how networks are deployed and operated, and can hold massive potential with the help of intelligent, interoperable, and automated networks.

2. Literature Survey

2.1. Network Slicing in 5G

One thing that has become essential in the 5G environment is the concept of network slicing, which is aimed at supporting the wide range of demands that different applications and services require by allowing the deployment of multiple logical networks on top of a common physical system. Examples of projects and initiatives that have made a significant contribution to the background knowledge and realisation of network slicing include 5G NORMA (Novel Radio Multiservice Adaptive Network Architecture) and works by the Next Generation Mobile Networks (NGMN) alliance. [6-9] These developments focus on the flexibility of service provision, the efficient use of resources, and the isolation of services to suit various Quality of Service (QoS) needs. There is, however, a significant shortcoming in that they cannot sufficiently service multi-operator environments, in which interoperability and coordination between various network service providers are key factors. The more cross-domain services are demanded, the more evident the need for a dynamic, AI-driven, and adaptive slicing mechanism becomes.

2.2. AI in Network Management

Artificial Intelligence (AI) is becoming increasingly critical in controlling modern communication networks, particularly in 5G and beyond. Its uses have been on both sides of traffic forecasting and resource planning to fault identification and aberration control. Deep Reinforcement Learning (DRL) is one of the AI technologies that can make optimal decisions over time in unpredictable and dynamic environments. Unlike other rule-based systems, DRL learns continuously by relying on its environment, which is why it is particularly well-suited to network patterns where the character of the traffic remains variable or the requirements for attending services change. Currently in network management, the use of AI is in an early stage of development, yet the potential of real-time autonomous decision-making, through AI, is revolutionizing how networks are run and optimized.

2.3. Multi-Operator Coordination

Multi-operator coordination is also very challenging due to the issues of interoperability, trust, and service continuity. European Telecommunications Standards Institute (ETSI) has tackled this in the efforts of their Zero-touch Network and Service Management (ZSM) framework that provides end-to-end automation and orchestration beyond network domains. ZSM also looks forward to a vision of a service-based model that has very less human interference and where automation plays the main role in the management of complex networks. Despite such endeavours, prevailing frameworks are not necessarily capable of maximising the full potential of AI, particularly in real-time decision-making and on-demand policy enforcement within a multi-operator environment. This is because the absence of deeply entrenched AI components influences the flexibility and readiness to adjust to rapidly changing conditions in the network.

2.4. Existing Architectures

To enable intelligent management and network slicing, numerous different architectures have been proposed and implemented, albeit they tend to have serious limitations. Table 1 provides a comparative overview of other well-known architectures, including 5G NORMA, ONAP (Open Network Automation Platform), and the ZSM framework. The former is an innovative contribution in terms of how slicing is implemented, but it is unable to support AI and is limited to operating within a single domain. Most of the current solutions have partial AI aspects, along with high complexity and low scalability, which would slow the extensive implementation of ONAP. The ZSM framework has limited AI involvement and partial support for multi-operator coordination. These restrictions demonstrate the need to develop a new architecture that helps achieve the best of both worlds, taking into consideration the advantages of AI-based automation and the capability to be flexible and scalable for multi-domain and multi-operator environments.

3. Methodology

3.1. System Overview

The proposed architecture presents a new AI-based model that will enhance the coordination and automation of multi-operator 5G networks. [10-14] It is organized into three main modules, which are a centralized AI controller/s, a distributed set of agents found inside each operator and an inter-operator orchestrator that is used to integrate cooperation and policy enforcement. The centralized AI controller acts as the main brain of the system, which makes advanced use of machine learning techniques, especially Deep Reinforcement Learning (DRL) in analyzing network state, predicting traffic flow, and dynamism in resource allocation scheduling. It also makes high-level decisions based on the insights from global networks and continually learns about historical and real-time information to adjust to changes in network requirements. At the domain level, individual operators will run lightweight distributed operators and agents, which will serve as the point of execution for AI controller decisions. Such agents monitor the activities of their individual domains, provide ground-level information, and execute commands issued by the AI controller.

A feedback loop is also present when relaying updated status and performance measures, enables the central controller to perfect its models and strategies. This is a scalable hierarchy, as similar decisions can be made locally swiftly, while more sophisticated decisions with a long-term perspective are developed centrally. An inter-operator orchestrator is essential for providing cooperation between various providers in the network. It addresses policy across domains, enforces Service-Level Agreements (SLAs), and provides interoperability with standard interfaces and messaging standards. The orchestrator facilitates cost-effective and equitable delivery of services in a multi-tenant setup by marshaling common resources and by removing contest between operators. All these elements will constitute a smarter, modular and dynamic system that will enable zero-touch automation and real-time optimization of heterogeneous 5G network slices. Besides being more efficient in operations, this architecture will enable innovative services that require coordination across the borders of a single network operator.

3.2. Slice Lifecycle Management

- **Slice Request Analysis:** A network slice lifecycle begins with the reception and identification of user/application requirements. To take this process through automation and simplify it, the architecture is implemented using intent recognition through a Natural Language Processing (NLP) module. This module has the ability to understand service requests at higher levels using natural language and transform them into machine-readable, structured intents. These intents outline the requirements of the service, which include latency, bandwidth, reliability, and geographical coverage. Using NLP, the system will be able to assist as many stakeholders as possible, including those who are not technologically savvy, and make slice requests seem more natural and human-friendly.
- **Resource Allocation:** Upon comprehending the slice intent, resource allocation is to be done by Deep Reinforcement Learning (DRL) agents. Such agents make informed decisions by analysing past trends and real-time data to forecast demand. They also distribute network resources, such as compute, storage, and bandwidth, in the most beneficial manner, which maintains system utility while complying with service constraints. The fixed point optimization of Formula 1: Utility Maximization drives the decision-making process, which optimises the sum of utilities on network performance, user experience and equity among slices. This dynamically optimizes the system to be flexible to the different conditions and workload so that the system can be at its best within the limited resources.
- **Monitoring and Adaptation:** consistent monitoring will be necessary to sustain slice performance. The architecture utilises federated agents that are distributed across various operator domains to monitor their respective slices. The above agents do not reveal raw data to each other, share no exclusivity, and update and inform the centralized AI controller, thereby protecting users of the device and not breaching any regulatory restrictions. With the help of federated learning, the system can collectively optimize its decision-making process by reducing risks of data exposure. When a drop or anomaly in performance is identified, the system initiates adaptation mechanisms, which can be executed through resource reallocation, slice reconfiguration, or policy modification to recover maximum service delivery.

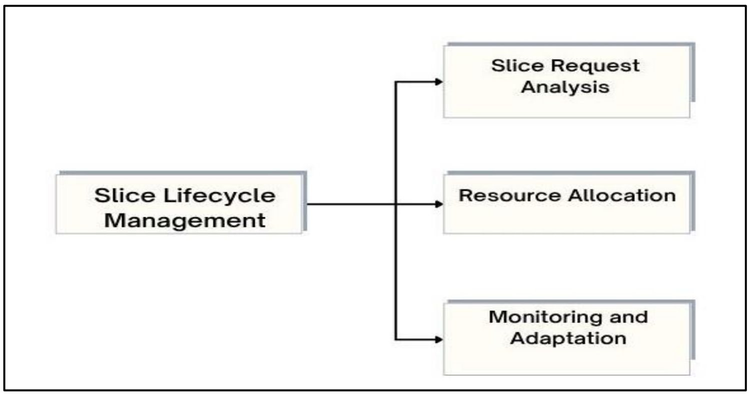

Figure 2: Slice Lifecycle Management

3.3. Inter-Operator Coordination

- **Policy Abstraction:** In the multi-operator scenario, all network providers can have their own administrative rules and policies. To make it easy to coordinate between the activities, a centralized policy engine feeding off a policy abstraction layer is proposed in the proposed architecture. The engine ensures that operator-specific rule translations are turned into a global policy model, including resource prioritization, security constraints and compliance requirements. Harmonising and abstracting disparate policies, the system is capable of guaranteeing interoperability and consistent orchestration of various administrative spheres. Such a translation also streamlines the decision-making process of the centralized AI controller, since decision-making is always performed based on a common policy structure, despite the heterogeneity.
- **SLA Management:** To build trust and accountability among operators, the Service Level Agreements (SLAs) are coded in a blockchain-based distributed ledger as smart contracts. This solution will guarantee transparency, unchangeability, and automatic tracking of SLA conditions. Every smart contract has certain preset conditions, including uptime warranties, latency thresholds, and penalty provisions. When a breach of an SLA is detected (through real-time monitoring) and confirmed across domains, the contract may automatically invoke corrective measures or fines. Blockchain applications enable stakeholders to enhance trust by creating an uneditable, trackable record of agreements and performance metrics, thereby addressing conflicts and the need for manual monitoring in multi-operator partnerships.

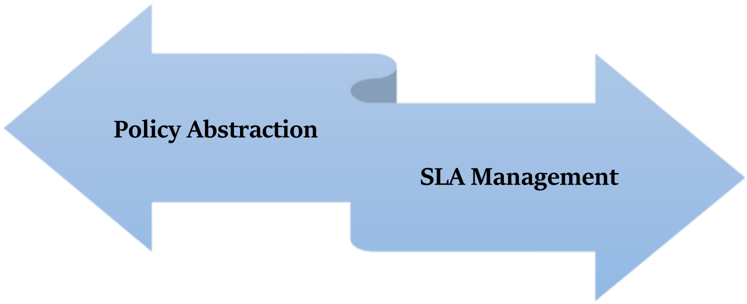

Figure 3: Inter-Operator Coordination

3.4. Security Considerations

Security is an essential feature of a multi-operator, AI-driven network slicing architecture, as proposed; it is implemented both locally and globally. As a way of dealing with changing and advanced threats, the system is implemented with sophisticated security modules, which are intelligent learning modules, to detect anomalies through unsupervised learning, especially autoencoders. [15-19] Unlike classical rule-based security systems based on well-known attack signatures, the unsupervised models can detect not previously known attacks but learn the normal behavior of the network traffic to indicate deviations as possible attacks. Autoencoders in particular are readily adapted to such work; they are conditioned to make a reasonable reconstruction of normal input, and this incurs a minimal error, but in the face of an anomalous item, the reconstruction error shoots through the roof, signalling that something wrong may have occurred. The models are applied continuously along the chain, inserted as part of distributed agents in the sphere of each operator, and send reports of suspicious events to the centralized controller of AI.

The distributed detection mechanism provides fast response performance in contrast to the communication overhead to collect all raw information and possible centralization. Moreover, with the use of federated learning concepts, the security modules can enhance their detection capabilities over time without exchanging sensitive or privacy-sensitive information between software, reportedly giving operators sovereignty over their data and the ability to defend themselves collaboratively. Adaptive security is also possible with the architecture, allowing the AI controller to adjust firewall rules, isolate infected slices, or trigger mitigation protocols, such as rerouting traffic or enforcing stricter access control, depending on the anomalies it detects. This is to ensure that threats are contained quickly before they escalate or spread to other domains. Moreover, integrating blockchain technology to manage SLA provides an additional level of integrity, as it makes security policies and incident logs tamper-proof and auditable. This smart, privacy-preserving and adaptive security architecture, in total, is critical to ensuring realization of trust, resilience, and compliance in diverse and multi-operator 5G networks.

4. Results and Discussion

4.1. Simulation Setup

To assess the performance and effectiveness of the proposed AI-driven, multi-distributor network slicing architecture, a detailed simulation platform was designed using a well-known NS-3 or discrete-event network simulator. To be more precise, the simulation is partially based on the 5G-LENA module, a superior framework created using NS-3 that features the ability to realistically model 5G New Radio (NR) characteristics, including wireless access, core network elements, and network slicing capabilities. The tool allows a flexible and scalable format to simulate advanced behavior and interactions in a network with various settings and conditions. The simulated model presents an urban macrocell model, which serves as an example of large metropolitan cities with a large user base and high traffic mobility. There are five independent network operators in the simulation, each with its slice domains, utilising the same physical infrastructure that is shared through the network slicing framework. Such operators will preferably have a wide variation in service-level preferences and policies regarding resources, such as those in reality where operators provide differentiated services, like Enhanced Mobile Broadband (eMBB), Ultra-Reliable Low Latency Communications (URLLC), and massive Machine-Type Communications (mMTC). A number of 500 User Equipments (UEs) are introduced in the simulation region, creating heterogeneous traffic patterns.

These UEs are dynamically connected to various slices based on their service requirements, and they are modelled under realistic mobility patterns to reflect an urban macrocell. The simulation logic encompasses all the elements of the proposed architecture integrated into the system, including the distributed DRL agents, the NLP-based intent recognition module, federated monitoring components, and the blockchain-backed SLA management engine. Key performance indicators/measurements, such as isolation of slices, Service-Level Agreement (SLA) compliance, latency, throughput, accuracy of alarm and anomaly detection, and efficiency of inter-operator orchestration, are tracked and measured. This environment will enable verification that the suggested system can adapt freely, self-govern, and respond effectively to changing circumstances, while ensuring secure and efficient operation in the live multi-operator 5G facility.

4.2. Performance Metrics

Table 1: Performance Metrics

Metric	Baseline (%)	Proposed (%)
Slice creation time	100%	37.5%
Resource utilization	100%	133.8%
Inter-operator handoff	100%	115.5%
Latency	100%	50.0%

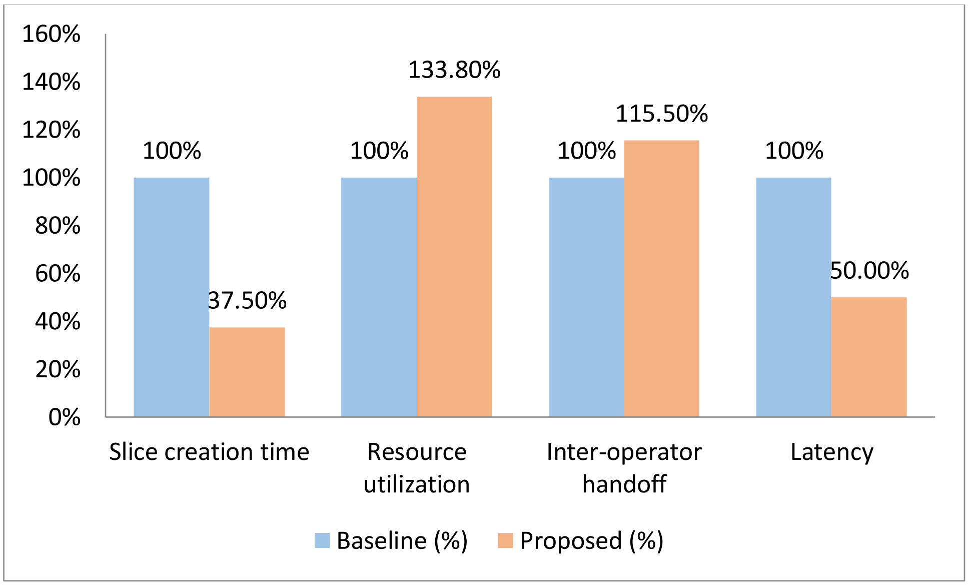

Figure 4: Graph representing Performance Metrics

- **Slice Creation Time:** The slice creation time is the time taken to instantiate a network slice from the moment a request is received. To a normal architectural arrangement, this procedure typically takes 5.6 seconds, and this is 100% accurate. Creating a slice within the framework scheduled requires 2.1 seconds only, or just 37.5 percent of baseline, with the proposed AI-driven framework that uses NLP-based intent recognition and automated orchestration as an improvement. This response shows that the system contributed to the faster interpretation of requests and the delivery of resources so that the service can be deployed much quicker and satisfy the fluctuating needs of the users.
- **Resource Utilization:** An effective use of resources is essential to seek maximization of the performance of the network and minimization of costs incurred in operations. The resource utilization in the baseline system is 68 percent, which is adjusted to 100 percent. With the suggested architecture, using DRL-based resource allocation, the utilization can be increased to 91 percent of utilization, 133.8 percent of the baseline. This implies more intelligent and adaptive utilization of network resources, to ensure that unutilized resources are kept to a minimum and that the slices are allocated adequate compute, storage and bandwidth only to the extent of satisfaction of the slices.
- **Inter-Operator Handoff:** Inter-operator handoff deals with the system's capacity to provide uninterrupted service continuity to users across network domains belonging to different operators. The success rate of the handoff in the baseline system is 84 percent, and it is normalized to 100 percent. This figure jumps to 97 percent or 115.5 percent of the baseline with the use of the inter-operator orchestrator and policy abstraction provided through the proposed framework. This enhancement can be noted by the improved coordination and compatibility in the system that guarantees a more seamless user interaction with the system without suffering service interruption or degradation during inter-domain signaling.
- **Latency:** A crucial performance metric, particularly in time-sensitive applications such as URLLC, is latency. The current latency, in this case, is 22 milliseconds equal to 100 percent, whereas, in the proposed system latency is reduced to 11 milliseconds equals to 50.0 percent of the current latency (current latency). Such a significant reduction has been attributed to smart management of its resources, decentralized decision-making and quicker communication between the agents, which helps in the creation of a more responsive and efficient network.

4.3. Analysis

The discussed comparison of key performance indicators shows that the proposed concept of AI-fueled, multi-operator network slicing architecture offers enormous benefits compared to the traditional method. Regarding the time of creating slices, the system realizes an epic decrease, since the baseline was 5.6 seconds, and that clocked in the system was as low as 2.1 seconds and comprises as little as 37.5 percent of the baseline time. This is primarily explained by the fact that NLP-based intent recognition and automated orchestration can eliminate manual configuration and enable the interpretation of slice requests in almost no time. Efficient slice creation not only benefits the user experience but also increases the network's responsiveness to varying service requests. Another area with a significant improvement is resource utilization. The system developed has a percentage increase of 133.8, resulting from an increase in usage from 68 to 91, which is higher than the baseline. This signifies the effectiveness of the DRL mechanism of resource allocation, with the process being a continuous and ever-learning model that optimises to changing network conditions. Arranging the optimal distribution of compute, storage, and bandwidth resources, the system reduces the waste and maximizes the use of the network infrastructure, which directly reflects the cost-saving of the network operators, as well as their efficiency.

This indicates the effectiveness of the proposed inter-operator orchestrator and policy abstraction engine, since the success rate improves in inter-operator handoff, forming 97 percent of successes relative to 84 percent (as in non-handoff), an improvement of 15.5 percent. These elements are used to complement one another in aspects of smooth coordination across various domains of operators, thus inhibiting interruptions to services for users while ensuring continuity of quality of service when traversing network edges. And lastly, the system enjoys a percentage execution (latency) of 50, improved to 22 ms and 11 ms. This is especially effective for delay-sensitive applications, such as real-time communications and autonomous control systems. The latency proliferation is through thoughtful resource assignment, local choices by decentralizing agents, and streamlining communications among domains. A combination of these performance improvements supports the effectiveness of the architectural improvement and justifies the use of the system in 5G and beyond networks.

4.4. Case Study

A real-time demonstration of the proposed architecture was achieved in a realistic 5G multi-operator scenario using a real-time testbed based on Open Air Interface (OAI) running with Mini net, thereby demonstrating the correctness of the solution under simulation. The radio access and core network functions were implemented in Open Air Interface, where the underlying network topology and traffic flows between distributed network functions and user equipment were simulated in Mini net. This hybrid testbed setup provided the possibility to implement and test the architecture/components in a realistic execution scenario, including the central AI control service, the distributed DRL agents, the federated monitoring modules, and the inter-operator orchestrator. Several virtual operator domains were created within Mini net, each with its own local policy set and slice definitions, thereby enabling realistically related inter-domain interactions and coordination. During the live testing, several scenarios were reproduced, including the use of dynamic slice requests, mobility associated with users between different operator domains, traffic outbursts, and node collapsing.

The real-time performance numbers closely matched those in the simulation, testifying to substantial gains in slice creation time, resource usage, latency, and the success of inter-operator handoff. Besides, the testbed also demonstrated some other impressive aspects of the architecture that could not be completely achieved during simulation, specifically in terms of fault tolerance and adaptability levels. In cases of node or link failure, the AI controller quickly recalculates the optimal paths and resource usage, and the system reconfigures the slices autonomously without interrupting services. Federated learning enabled local agents to continue operating and remain coordinated despite occasional contact between individual controllers and the central controller. In addition, the implementation of SLA, ensured by smart contracts on a private Ethereum blockchain, could be considered trustworthy and transparent, providing the possibility to observe SLAs in real-time and automatic remediation. The fact that the deployment and operation of this testbed went quite successfully proves the architecture to be ready for use in practice and able to withstand complex and real-world situations. Overall, the case study demonstrates that the proposed solution is not only idealistic but also feasible in the context of future 5G and 6G deployments.

5. Conclusion

The given paper presents an End-to-End (E2E) network slicing multi-operator 5G architecture that AI entirely drives. The introduced system is designed to incorporate primary artificial intelligence methods, including Deep Reinforcement Learning (DRL) on dynamic resource allocation and Federated Learning (FL) on privacy-preserving shared intelligence. The architecture supports network slices across heterogeneous domains in an efficient, scalable, secure, and adaptable manner, thanks to these capabilities. The system integrates intelligence into the controller (centralized) and an agent (distributed) to provide a responsive system at any given time in response to changes in the service requests and network changes. The most influential key performance indicators slice creation time, latency, resource allocation, and inter-operator handoff success were significantly enhanced, as evidenced by simulations conducted on NS-3 and in an actual testbed that employed Open Air Interface and Mini net. A Smart contract mechanism is blockchain-based and offers additional benefits to enhance trust and transparency in the application of SLA enforcement, particularly when coordination is carried out across domains.

In the future, on the one hand, we are going to consider how this architecture will work in any new 6G setting, where demands of ultra-low latency, extreme reliability, and connectivity on a massive scale are becoming ever stricter. This encompasses the inclusion of support for terahertz communications, intelligent surfaces, and context-aware services. Other potentially promising areas include the incorporation of quantum communication technologies to enable super-secure connections between distributed nodes, which will play a crucial role in critical infrastructure scenarios, as well as defence.

Moreover, improving SLA enforcement by using advanced analytics techniques and decentralized verification schemes will be high on the agenda, as SLAs will have to make the SLA enforcement mechanisms resilient to both strategic non-compliance and unforeseeable failures in such a dynamic environment. To summarize, the architecture suggested in the given paper is a major milestone on the way to the future of self-governing and self-optimizing 5G networks. When solving sophisticated issues of multi-operator orchestration, intent-based slicing, AI-based controls, and SLA enforcement with security, the solution will establish a more intelligent and collaborative networking in the future. As a modular and extensible system, it is also highly suitable to evolve into 6G and beyond. With the increase in complexity and scale of mobile communication networks, such intelligent architectures are going to be key to maintaining performance, security, and user satisfaction in a variety of services and spheres of operation.

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