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Improvement of 5G Core Network Performance using Network Slicing and Deep Reinforcement Learning

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ABSTRACT- Users have increasingly been having more use cases for the network while expecting the best Quality of Service (QoS) and Quality of Experience (QoE). The Fifth Generation of mobile telecommunications technology (5G) network had promised to satisfy most of the expectations and network slicing had been introduced in 5G to be able to satisfy various use cases. However, creating slices in a real-life environment with just the resources required while having optimized QoS has been a challenge. This has necessitated more intelligence to be required in the network and machine learning (ML) has been used recently to add the intelligence and ensure zero-touch automation. This research addresses the open question of creating slices to satisfy various use cases based on their QoS requirements, managing, and orchestrating them optimally with minimal resources while allowing the isolation of services by introducing a Deep reinforcement Machine Learning (DRL) algorithm. This research first evaluates the previous work done in improving QoS in the 5G core. 5G architecture is simulated by following the ETSI NFV MANO (European Telecommunications.

Standards Institute for Network Function Virtualization Management and Orchestration) framework and uses Open5G in 5G core, UERANISM for RAN, Openstack for Virtual Infrastructure Manager (VIM), and Tacker for Virtual Network Function Management and orchestration (VNFMO). The research simulates network slicing at the User Plane Function (UPF) level and evaluates how it has improved QoS. The network slicing function is automated by following ETSI Closed Loop Architecture and using Deep Reinforcement Learning (DRL) by modeling the problem as a Markov Decision Problem (MDP). Throughput is the Reward for the actions of the DRL agent. Comparison is done on the impact of slicing on throughput and compares models that have not been sliced, the ones that have been sliced and combined to work together, and models with slices that have been assigned more bandwidth. Sliced networks have better throughput than the ones not sliced. If more slices are load-balanced the throughput is increased. Deep Reinforcement Learning has managed to achieve the dynamic assigning of slices to compensate for declining throughput.

Keywords: 5G, 5G Architecture, ETSI NFV MANO, Network slicing, QoS, Reinforcement learning, User plane functions.

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1. INTRODUCTION

The COVID-19 pandemic accelerated hybrid working as a normal working policy. This has made users have requirements for new use cases and 5G has been proposed to be able to deliver the use cases with transformative experiences. [1]. Users have therefore opted to use 5G to be able to benefit from the promised enhanced Quality of experience (QoE), network reliability, and performance. [2]. For this to be a reality then there is a need to ensure effective and improved QoS on the 5G networks. Contrary to previous generations of mobile networks, for 5G evolution has been much more. Apart from just increasing data rates and more bandwidth, the focus shifted from just individual consumers and includes enterprises, industries, etc. [2]. This significant shift has made 5G to be able to deliver new use cases as per the user's requirements. International Telecommunication Union- Radiocommunication Sector (ITU-R) has prioritized the following 3 use cases as the main ones: Enhanced mobile broadband (eMBB); Massive machine-type communications (mMTC); Ultra-reliable and low-latency communications (URLLC). [1]. To make the use cases a reality, advanced technologies need to be applied. For example, In the first use case, eMBB, the International Telecommunication Union (ITU) in its report identified core networks virtualization, Radio spectrum, and the backhaul that connects the core and radio network to be incredibly significant in rolling out 5G. Other enablers to achieving the use cases also included network function virtualization (NFV), software-defined networking

(SDN), Cloud computing (CC), and Mobile edge computing (MEC). [3]. The use cases have resulted in an architecture with various functionalities to meet its objectives. [4]. The various use cases have also come up with various services that have varying and stringent QoS requirements. To address this challenge of having various services with different user requirements, the network slicing concept came up.[5]. This entails having logical sub-networks on a single physical infrastructure. [6]. Slicing can be done at various levels in a 5G network.[7]. Since this research focuses on the improvement of network performance by looking at QoS, slicing is done by sharing the same Radio Access Network (RAN), Access and Mobility Function (AMF), and Session Management Function (SMF) but can have multiple User Plane Function (UPF)s. However, managing the slices dynamically and optimally has been a challenge. The authors in [8] proposed that apart from just doing network slicing to improve QoS, the Network Functions [NF] should be put closer to the users to meet the requirement of reliability bandwidth, and latency. However, this can increase the costs and number of NFs. [9]. Authors in [7] propose that placement of NFs optimally is crucial to cost-effectively offering QoS and [8] had resolved on how to place the UPFs cost-effectively. However, there is still a highlighted challenge in knowing the number of UPFs needed to handle the data plane traffic, in a virtualized environment. [9]. The QoS requirements can also be very complex and [10] proposes a 5G/6G core architecture that is flexible, customizable, and can be used to optimize network slices.

Most of the previous research had focused on the radio access part however, this research focuses on the core network and more specifically the user plane functions. To properly manage the complex QoS by dynamically selecting slices and dynamically placing and selecting UPF then massive intelligence is required and this needs to be derived from available data in the network. [1]. Artificial Intelligence (AI) is therefore expected to enhance the 5G network performance by analyzing the data and providing actionable insights to manage and orchestrate network resources and provide intelligence to systems.[1]. Previously the network management used Self Optimized Networks (SON) due to two reasons.[10]. First is increasing demand by consumers for multiple services with the operators being under pressure to reduce Go to Market time while reducing costs to remain competitive. Secondly, the networks have become overly complex with very many nodes in the ecosystem thus making the traditional field trial approaches impractical. However, 5G contributes by expounding how machine learning is used with SON to improve the Operations, Administration, and Maintenance (OAM) activities [11]. It shows how the tasks are simplified to improve the network performance proactively. Machine Learning brings the perspective of improving network performance by learning from experience and automating the network. Deep Reinforcement Learning has been used to scale UPF resources depending on Protocol Data Units (PDUs) required by customers controlled by a scaling algorithm [12].

The contribution of this paper includes:

- Evaluating the previous works done in improving QoS in 5G core.
- Evaluating a sliced model against an unsliced baseline model based on throughput.
- Evaluating the effect of load balancing in a sliced network
- Integrating Deep Reinforcement Learning to aid in network slicing, determine the number of UPFs required, and launch the number of UPFs required.
- Evaluating the effect of the automated model on the QoS of the network.

The highlighted contributions of this paper are significant in this area of research. Enhancing the Qos of the core network by minimizing delay, maximizing throughput, and promoting load-balancing has great benefits as end users get superior experiences when utilizing services such as 4K video streaming and augmented reality. The slicing in 5G is also essential as it allows different services with varying QoS requirements to be given different priorities and this allows mission-critical services such as remote surgery and communications during emergencies to have guaranteed QoS priority. The fact that the system can intelligently and dynamically respond in slice creation to enhance the QoS greatly impacts the core network of 5G.DRL has brought the intelligence that will assist in ensuring dynamically optimized QoS by efficiently creating more or reducing slices in real-time and having optimal UPFs required that can meet defined QoS thresholds, load-balancing traffic across the UPFs, and is, therefore, able to maintain service quality. The intelligence of the DRL also makes it possible to optimally manage trade-offs in minimizing delay while maximizing throughput. Additional benefits such as congestion control and efficient resource utilization are derived. This paper is thus significant in this area of research.

2. BACKGROUND

2.1. Related Works

There has been mobile Telecommunications development evolution from 1G to 5G. Mobile Telecommunications protocol development is usually done by an umbrella body of standards organization called 3GPP. In the 4G, commonly referred to as LTE, the main aim has been to provide mobile broadband services. There has however been a requirement for new use cases from the network by the users such as the Internet of Things, health, etc. [13]. Peter Rost et al highlight that to achieve these use cases the network needs to evolve, have some intelligence, and be more programmable. The networks therefore need to develop with two main objectives; Different tenants sharing network resources while offering different services and being able to provide multiple services while being aware of the environment and actual service requirements. To obtain the objectives, the authors note the importance of introducing some technologies into the network; Decompose network function into smaller flexible blocks called Network Functions which can offer diverse services while having the ability to be optimized by using different software; Virtualize the network functions and separate hardware from software; introduce network slicing where different operators or users of the network have their logical network but sharing same infrastructure; have software-defined management, control and orchestration of the network; separate the control and data plane and transfer some functionalities to the cloud. The introductions of the technologies produce some benefits to the network such as flexibility, unified management, simplified operation, and enabling network innovation. However, there is still a need for one flexible and highly dynamic mobile network architecture that entails the integration of various technologies, use cases, and deployments with each node implemented as virtual network functions tailored to its specific use. The multiple use cases and services with the limited network infrastructure resources necessitate the physical infrastructure to be divided into multiple logical networks, a concept called network slicing. [14] explores the network slicing concept by proposing a new architecture utilizing SDN and NFV.[7] proceeds to look at various ways of implementing network slicing. They first start by reviewing the slicing in different ways (service, infrastructure, and network). They then proceed to dissect the slicing at the infrastructure level and provide 3 different architectures for slicing. The authors in. [8] looked at slicing in multi-domain wireless network infrastructure and proposed a mathematical model for network slicing creation and mapping onto the physical infrastructure in a two-step format: placing the network functions and choosing the links connecting them. .[14] reviews the process of slicing that involves the creation, isolation, and management of slices and elaborates that introducing both SDN and NFV on the access and core improves resource management, utilization, and latency. The technologies also enable the scalability and elasticity requirements to be met. [15]. The authors look at a comprehensive framework and network slicing techniques and how slicing can be used in resource management to improve QoS in 5G. The authors in [16] propose an access selection scheme for the slices. The authors in [17] undertake simulations on network slice creation and isolation and present the results.[18] also, look at how slicing is implemented in a multi-slice 5G Core environment by provisioning slices in User Plane Functions using varying QoS requirements and comparing it to an unsliced core. The authors in [19] utilize the Game Theory Model to optimally select slices in the UPF in 5G environments thus minimizing the overall service delay. [20] proceeds to solve the two main problems of UPF: location and optimal number required in 5G networks. To ascertain the necessary position and quantity, the authors represent the User Plane Functions Placement (UPFP) as a Mixed-Integer Linear Programming (MILP) issue and suggest two optimization models that take user mobility, latency, and reliability into account. Two services are selected to evaluate their performance. Managing the slices dynamically and optimally has been a challenge. The authors in [8] proposed that apart from just doing network slicing to improve QoS, the Network Functions [NF] should be put closer to the users to meet the requirement of reliability bandwidth, and latency. However, this can increase the costs and number of NFs. [9]. Authors in [7] propose that placement of NFs optimally is crucial to cost-effectively offering QoS and [8] had resolved on how to place the UPFs cost-effectively. However, there is still a highlighted challenge in knowing the number of UPFs needed to handle the data plane traffic, in a virtualized environment. [9]. The QoS requirements can also be very complex and [10] proposes a 5G/6G core architecture that is flexible, customizable, and can be used to optimize network slices. The various use cases, offering of multiple services, and network slicing have made mobile networks to be very complex. There is therefore a need to manage the network efficiently with all this complexity with optimal network performance. In previous generations [2G,3G, and 4G), Self-Optimized Networks [SON] Technique has been widely researched as the solution for network management [10]. However, Ali Imran et al highlight that due to the new technologies in 5G, the complexity, cost, and the high expectation of Quality of Experience, SON needs a new approach for 5G. The authors highlight the challenges of SON in 4G and then propose a new framework that relies on big data. SON needs to be self-organizing with end-to-end behaviour network intelligence.[10].SON, as it is used in 4G, has various challenges; underutilized intelligence in that it operates based on full or partial knowledge of a problem yet this process cannot be used to dynamically predict system behaviour in the live environment required for the best quality of experience; need for self-coordination as 5G is already decomposed into small blocks called Network Functions which should not conflict for stable network operation; need for more transparent SON with holistic approach where there is a view of various vendors and being looked at In full including for users. To have the intelligence then massive data is required. The authors propose a framework to collect the data, the type of data to be collected, and from which level. However, to provide end-to-end network intelligence, the data needs to be mined using Machine Learning tools. To use the massive data in 5G, [11] contributes by expounding how machine learning can be used with self-organized networks to improve network management. It shows how the tasks are simplified to improve the network performance proactively. Machine Learning is highlighted as gaining interest due to two reasons. First is increasing demand by consumers for multiple services with the operators being under pressure to reduce Go to Market time while reducing costs to remain competitive. Secondly, the networks have become very complex with many nodes in the ecosystem thus making the traditional field trial approaches impractical. Machine Learning brings the perspective of improving network performance by learning from experience and automating the network. However, there are still some open challenges that are highlighted for the network to improve performance and fully automate network management. [11] highlights the research challenges as follows:

• There is a need to use real network data from operators or simulate real data that can be used in extracting experience by using Machine Learning to identify what needs to be optimized.
• Deep learning has been used in solving complicated applications but has not been used in network management of the complex 5G ecosystem. With the availability of data from the 5G ecosystem, the impact of deep learning on network management should be explored.
• There is a need for autonomous network management of multi-technology networks which includes different Radio Access Technologies or networks with self-awareness and intelligence.

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• Autonomous network management of novel software and virtualized architectures with the ability to adapt to environment conditions i.e., not only reacting to failures but also adapting to demand and making predictions using data analytics to enhance network management and improve performance.

DRL, a subset of machine learning has been proposed to manage the network slicing in 5G. The authors in [3] contributed to the DRL and the 5G network slicing by conducting a comprehensive survey looking at the DRL framework, virtualization, and network slicing. They proceeded to review the challenges in 5G network slicing and how to incorporate DRL in addressing them. In [20] the authors looked at how ML is used to provide an adaptive and flexible 5G network by providing the intelligence to adapt, forecast, and recover from fluctuation in the network. The authors propose an RL algorithm in a multi-slice environment to partition the slice request and consider the constraints such as delay, location, etc with the performance comparison showing that 99.9 percent of the time there are some savings in processing the requests. In [21] the authors further explore how to scale DRL Learning in scaling UPF instances. They present a method that modifies the proximal policy optimization (PPO) algorithm and formulates a reward function with a threshold. Additionally, they use a support vector machine (SVM) classifier to handle situations in which the stochastic policy causes the agent to propose an undesirable course of action. The method works better than the integrated Horizontal Pod Autoscaler (HPA) in Kubernetes, according to extensive numerical results. DRL could save 2: 7-3: 8 percent of the average number of Pods, while SVM could achieve 0: 7-4: 5 percent savings compared to HPA. [22] had also looked at using DRL in the RAN with the Algorithm to improve the RF antenna performance. Deep Reinforcement Learning has been used to choose VNF instances optimally while implementing optimum QoS.[28]. The optimal Virtual Network Functions can be implemented to achieve optimum QoS. [23]. Most of the research has been around Radio Access.[7] proposes a mechanism of scaling 5G core network resources by anticipation of changes in traffic load using Machine Learning to forecast. Real datasets are used for two neural networks, and then a comparison is made. The results indicated forecast-based scalability mechanism outperforms the threshold-based solutions, in terms of latency to react to traffic change and delay to have new resources ready to be used by the VNF to react to traffic increase. There is an open challenge to use the trained RNN to estimate the number of UPF (User plane 5G core network function) needed to handle the data plane traffic, in a virtualized environment. Based on previous work there is a need to use DRL for dynamic network management to improve network performance in 5G and validate this using real datasets. There is also a need to use DRL in managing network slicing and having optimal UPF instances to achieve consistent QoS. Additionally, there is a need to have a more predictive approach that responds to real-time conditions.

2.2. Mobile Network Evolution

The evolving user requirements have necessitated the evolution of mobile telephony networks in terms of architecture, capacity, and speed. The 1st Generation of mobile telecommunications technology (1G) satisfied the need to communicate using voice. It was based on analog signal transmission and could only achieve a speed of up to 2.4kbps. It utilized Frequency Division Multiple Access (FDMA) that allowed each user to use their band of frequency for communication and this had poor spectral efficiency. To address the limitations,2nd mobile telecommunications technology (2G) came in with the introduction of Digital speech encoding.[22]. In addition to FDMA, 2G introduced Time Division Multiple Access (TDMA) and Code Division Multiple Access (CDMA). TDMA divided the channels into timeslots while CDMA allowed the information to be sent as unique codes and this greatly enhanced the spectral efficiency. This allowed users to send text messages and some amount of data as the speeds could go up to 100kbps. The second generation(2G) also introduced better modulation schemes such as the Gaussian Minimum Shift key (GMSK) and Quadrature Phase Shift Keying (QPSK). This allowed utilization of the same bandwidth while transmitting more data. The third generation(3G) came in to increase the data speeds and thus the cellular architecture changed, CDMA was more prominent, and packet switching was introduced. The users could now use mobile internet browsing, video calls, and multimedia services since the speeds could go up to 10Mbps. To further increase the capacity and reduce latency 4G came. The architecture had evolved, and it became all-IP with some new components such as eNodeB introduced into the architecture. Users were now able to stream High-Definition videos and quicker data transfers with speeds going up to 100Mbps.Fourth Generation of mobile telecommunications technology(4G) used the more efficient Orthogonal Frequency Division Multiplexing (OFDM) which allowed parallel data transmission in various subcarriers on the same channel. The introduction of the Fifth generation of mobile telecommunications technology (5G) further reduced latency to microseconds, had high speeds of some Terabytes per second but most importantly was able to satisfy more use cases in the network. 5G introduced technologies such as Beamforming and massive Multiple-Input Multiple-Output (mMIMO). Beamforming has helped in minimizing interference.[24]. 5G also enabled simultaneous connection of multiple devices as part of IoT. This has resulted in a lot of data and this research looks at utilizing this intelligence to be able to satisfy more use cases efficiently.

2.3. 5G Architecture

5G had promised huge throughput, connection to a large number of devices, several business services, and low latency.[3]. To achieve all these,5G classified the use cases as mMTC, UrLC, and eMBB[25]. Advanced technologies have been introduced in 5G such as software-defined networks (SDN) for programmability and network orchestration, Network Function Virtualization (NFV)to offer the services,[4] and Mobile Edge Computing(MEC) for scalability and to reduce latency.[3] had explored this use cases and identified that to further achieve on its vision then designing and implementation of the network must shift. The multiple use cases and services with the limited network infrastructure resources necessitate the physical infrastructure to be divided into multiple logical networks, a concept called network slicing.

[26] explores the network slicing concept by proposing a new architecture utilizing SDN and NFV.[7] proceeds to look at various ways of implementing network slicing. They first start by reviewing the slicing in different ways (service, infrastructure, and network). They then proceed to dissect the slicing at the infrastructure level and provide 3 different architectures of slicing. The third option entails having a shared AMF, SMF and multiple UPFs. To be able to satisfy the requirements and diverse use cases,5G must be flexible and highly dynamic, and the architecture therefore has different nodes implemented as Virtual network functions. The control plane (CP) is split from the user plane (UP), and this makes it highly programmable. Due to the NFV, 5G architecture consists of Network Functions (NF) where each Network function performs different functions. [4]. The SDN and separation of CP and UP also make the architecture complete with the UPF being the only NF on the UP and the other NFs being on the CP and include: Network Slice Selection Function (NSSF), Access and Mobility Management Function (AMF), Policy Control Function(PCF), Authenticate Server Function(AUSF), Unified Data Management(UDM), Unified Data Repository(UDR), Network Exposure Function(NEF). The Network Functions in the 5G control plane communicate using a common interface. The non-roaming architecture is defined by 3GPP as per Figure. 1. Due to the modularized nature of 5G, Open5GS has been used to simulate the 5G core network with UERANISM used to simulate the RAN network.

2.4. Network Slicing

Network slicing can be defined as the process of creating slices in the network according to the needs of different end users. [26]. It involves having logical sub-networks in a physical infrastructure to be able to address different use cases or service requests. The authors in.[8] looked at slicing in multi-domain wireless network infrastructure and proposed a mathematical model for network slicing creation and mapping onto the physical infrastructure in a two-step format: placing the network functions and choosing the links connecting them. Each slice has different attributes referencing multiple use cases.[26] reviews the process of slicing that involves the creation, isolation and management of slices and elaborates that introducing both SDN and NFV on the access and core improves resource management, utilization, and latency. The technologies also enable the scalability and elasticity requirements to be met. [14]. The authors look at a comprehensive framework and network slicing techniques and how slicing can be used in resource management to improve QoS in 5G. The authors in [15] propose an access selection scheme for the slices. The authors in [17] undertake simulation on network slice creation and isolation and present the results.[18] also look at how slicing is implemented in multi-slice 5G Core environment by provisioning slices in User Plane Functions using varying QoS requirements and comparing it to an unsliced core. The performance of the multi-slice architecture is better in terms of throughput. Slicing can be done at various levels and for the sake of this research, slicing will be done as per *figure 2*. However, one of the main problems in slice simulation had been the creation and management of slices as well as how to secure them. [18] had looked at a possible solution to this problem and had looked at the ETSI NFV MANO Framework to be able to create slices since it had been used to enable network functions.

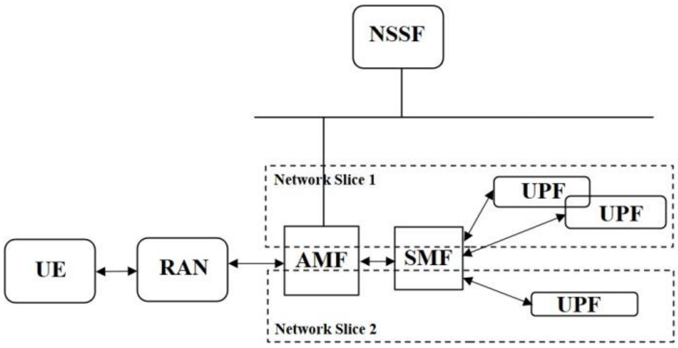

Figure. 2 5G Network Slicing Architecture [4]

2.5. Network of Functions

Network slice comprises of combination of multiple virtualized network functions to operate end to end [13]. The network functions are implemented on top of the same hardware. The VNFs are chained together although mutually isolated.

2.6. ETSI NFV MANO FRAMEWORK

ETSI NFV MANO has provided the framework for the orchestration and management of 5G and provisioning and configuration for the Virtualized network functions with its infrastructure. [20]. The architecture consists of three major components:

Fig. 2 5G Network Slicing Architecture [4]

• Virtualized Infrastructure Manager: This manages the Network Virtualization Functions Infrastructure such as network, compute, and storage and maps the hardware resources to the virtual resources using the virtualization layer.
• NFV Orchestrator: These orchestrate the Network Virtualization Functions Infrastructure resources and manage the Network Services and deployment of templates for the NFs.
• VNF Manager: These manage the VNFs by creating, terminating, or modifying them.

The architecture is as per *figure 3*. Since the framework gave the ability to manage the Network Functions, it will still be used to create slices. For this simulation, OpenStack is used as a VIM and OSM/Tacker as the VNFM/NFVO.

2.7. ETSI NFV MANO Based Slicing

The ETSI NFV MANO framework provides the platform for creating slices. Using the framework and Control and User platform Separation, the overall architecture is subdivided into 3 parts:

- User Plane
- Control Plane
- Management Plane

In this research, we look at having different slices with different QoS requirements and comparing performance with an architecture that is not sliced. We later incorporate Deep Reinforcement to automate the slicing in real-time.

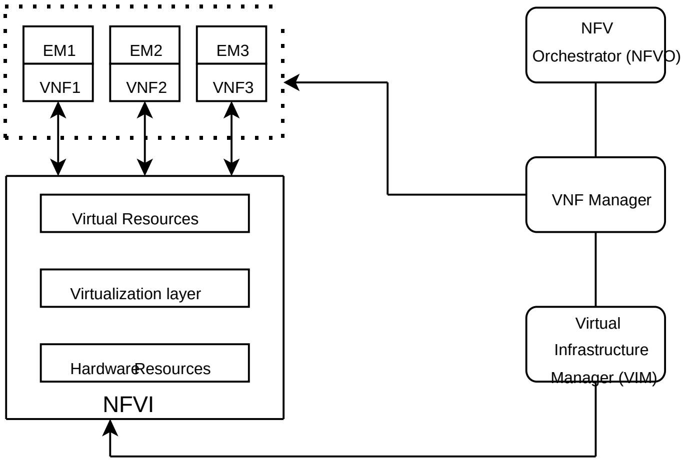

Figure. 3. ETSI NFV MANO FRAMEWORK [22]

2.8. ETSI Closed Loop Architecture

To ensure the slice creation is automated we looked at the zero-touch automation using Closed-Loop Automation (CLA). This uses feedback signals in monitoring and self-regulation. It uses a closed feedback loop. By leveraging Intents as its information objects, components utilized within a CLA can exchange information more effectively and simplify their interactions with one another. The CLA is commonly achieved in the management domain by the chaining of several management services, including knowledge base management, intentions and policies, orchestration, analytics of management data, etc. The purpose of CLA is to create an autonomous system that can perform and monitor itself continually, as well as assess and take appropriate action when the objectives are not met. The primary functional phases that the CLA for the NFV domain follows are as follows: gathering monitoring and management data (as input), carrying out actions because of the CLA (as output), and performing any necessary analysis and decision-making procedures in between. These steps are frequently circular in nature. Any component of the NFV architectural framework, the orchestration and management layers above NFV-MANO, or combinations of both, may be involved in the CLA logic and procedures. Figure 4 shows this CLA notion in the NFVO domain.

2.9. User Plane Function

The two main technologies in 5G: SDN and NFV bring a lot of significance to the architecture. SDN enables the separation of control and forwarding planes whereas NFV enables decoupling of software functions from hardware and virtualization of network functions. [3]. This therefore enables the implementation of various functionalities as Network Functions such as SMF, and AMF. This research focuses more on user plane functions whose main functions include Quality of service and policy enforcement. [7] had looked at various levels of network slicing and one of the options was doing slicing at the UPF level. This research therefore implements slicing at the UPF level to improve QoS and overall core network performance. The authors in [27] utilize the Game Theory Model to optimally select slices in the UPF in 5G environments thus minimizing the overall service delay.[28] proceeds to solve the two main problems of UPF: location and optimal number required in 5G networks. To ascertain the necessary position and quantity, the authors represent the User Plane Functions Placement (UPFP) as a Mixed-Integer Linear Programming (MILP) issue and suggest two optimization models that take user mobility, latency, and reliability into account. Two services are selected to evaluate their performance. This research builds on previous research by doing slicing at the UPF and optimizing the number and location of UPFs required.

2.10. Deep Reinforcement Learning

The massive amount of data and stringent QoS requirements of the different services bring considerable intricacy to the coordination and administration of multi-slice domain architecture. The dynamic placement of UPF and optimization of the number of UPFs also bring an operation complexity in the 5G network. Artificial intelligence [AI] is required to bring intelligence that can handle this complexity. AI uses smart agents to understand the environment and acts based on experience. The learning can be categorized as supervised, unsupervised, semi-supervised, and reinforcement learning [RL]. RL is done based on interaction in a trial-and-error manner. [3]. Since the agent needs to explore the environment, reinforcement learning is one of the best suited based on its interaction with the environment. In essence, the Deep Learning agent will monitor the state of the 5G environment and monitor its state (i.e., throughput and delay) and then create an action to add more slices or select specific slices based on the output and policies. The 5G environment reacts and the agent receives a reward and determines the next action. The experiences derived from the interaction are the data that the agent uses to train the Model’s policy. The agent uses the updated state and reward to select the next action. The authors in [3] contributed to the DRL and the 5G network slicing by conducting a comprehensive survey looking at DRL framework, virtualization, and network slicing. They proceeded to review the challenges in 5G network slicing and how to incorporate DRL in addressing them. DRL is a subset of Machine Learning that combines Deep Learning (DL) and RL. RL is a subset of ML that uses an action and cumulative reward. In [28] the authors looked at how ML is used to provide an adaptive and flexible 5G network by providing the intelligence to adapt, forecast, and recover from fluctuation in the network. The authors propose a RL algorithm in a multi-slice environment to partition the slice request and consider the constraints such as delay, location, etc with the performance comparison showing that 99.9% of the time there are some savings in processing the requests. In [26] the authors further explore how to scale DRL Learning in scaling UPF instances. They present a method that modifies the proximal policy optimization (PPO) algorithm and formulates a reward function with a threshold. Additionally, they use a support vector machine (SVM) classifier to handle situations in which the stochastic policy causes the agent to propose an undesirable course of action. The method works better than the integrated

Horizontal Pod Autoscaler (HPA) in Kubernetes, according to extensive numerical results. DRL could save 2: 7-3: 8% of the average number of Pods, while SVM could achieve 0: 7-4: 5% savings compared to HPA. [19] had also looked at using DRL in the RAN with the Algorithm improving the performance of the RF Antennas. This research therefore focuses on how to use DRL to dynamically select UPF slices and optimally determine the number of UPF instances required to improve the QoS performance of the 5G core network. RL has the sole aim of an agent learning how to evolve in an environment. RL has been modelled as a Markov Decision Process (MDP) with the following elements:

1. Agent – The Decision Maker
2. Environment- The state of the surrounding
3. States- All the possible states of the environment are denoted as S.
4. Action- The actions by the agents are denoted as A.
5. Reward- The benefits an agent gets from its previous actions in the previous state.

The MDP is modelled as a 5-tuple ($A,S,\{Psa\},R,\gamma$) where:

- S = the set of states
- A = the set of actions.
- $\{Psa\}$ = state transition probabilities for $s \in S$ and $A_t \in A$
- $\gamma \in [0,1]$ = discount factor
- $R: S \times A \longrightarrow R$ or $R: S \longrightarrow R$ = reward function that the algorithm wants to maximize.

The process of selecting an action in each state, receiving a reward, and transitioning to a new state happens sequentially creating a trajectory. The agents' goal is to maximize cumulative rewards. We assume the set has a finite number of elements. At each time step t = 0,1,2...., the agent gets some states $s \in S$. The agent chooses an action $A_t \in A$ based on this state. The state-action pair (S_t,A_t) is thus obtained. The environment is then changed to a new state $S_{t+1} \in S$, and time is increased to the following time step t + 1. At this point, the action A_t performed in state S_t earns the agent a numerical reward $R_{t+1} \in R$.

Mathematically,

$$F(S_t,A_t) = R_{t+1} \qquad (1)$$

A representation of the route would be S_0, A_0, R_1,S_1,A_1,R_2,S_2,A_2,R_3.The random variables R_t and S_t have well-defined probability distributions since the sets S and R are finite. These distributions are defined as follows: The probability of changing to state s' with reward r from taking action a in state s is $P(s',r|s,a) = Pr\{S_t = s'; R_t = r|S_{t-1} = s, A_t - a = a\}$ for all $s \in S$, $r \in R$ and $A_t \in A$.

The following issues need to be explored to model an MDP:

1. How likely is it that an agent will choose a particular action from a particular state?
2. To what extent does an action or state benefit the agent?

For the questions to be answered we need to discuss various concepts:

Expected return: The agent's goal is to maximize the returns and calculate the cumulative returns of the present and future. The future is predicted using a discount rate.

Policies: A formula π: $S \longrightarrow A$ that associates states with actions is called a policy π. If we are given a state s and we want to do an action $a = \pi(s)$, we execute the supplied policy π.).

Value: The expected return from beginning from states at time t and doing action a, adhering to policy π, is the value of state s under policy π. The value function $V\pi$ is defined as follows:

$$V^{\pi}(s) = E[R(s_0) + \gamma R(s_1) + \gamma^2 R(s_2) + \dots |s_0 = s, \pi] \qquad (2)$$

Optimal state value function: This involves getting the max state value function using the optimal policy and is normally referred to as Q-learning. A policy π is better than or the same as policy π' if the expected return of π is greater than or equal to the expected return of π' for all states. This is characterized using the Bellman equation.

$$V_{\pi}^{*}(s) = R(s) + \max_{a\in A} \gamma \sum_{s' \in S} P_{sa}(s') V^{\pi *}(s') \qquad (3)$$

Value iteration algorithm: The algorithm is as follows:

• Initialized using 0

$$V_0(s) = 0 \qquad (4)$$

• Iteration of values based on preceding values:

$$V_{i+1}(s) = R(s) + \max_{a\in A}[\sum_{s' \in S} \gamma P_{sa}(s') V_i(s')] \qquad (5)$$

Exploitation versus exploration: An agent uses the Epsilon greedy strategy to learn the environment where the probability that an agent will explore the environment instead of exploiting it is defined. The probability is initially set to 1.

3. MATERIALS AND METHODS

3.1. Overview of the Architecture

The proposed architecture has 3 components.

- User Plane- The User plane where the slices are created includes the UPF. The User Plane is simulated as part of Open5GS simulation in the core network.
- Control Plane- The CP will include the 5G core components. However, for the sake of this simulation, our interest is in the RAN, AMF, SMF, and NSSF.
- Management Plane -The part that will do the management and orchestration will have 3 components:
- VIM which is stimulated using Open-Stack.
- VNFM which pairs Tacker and Open-Source MANO(OSM)
- NFVO which uses Open-source MANO(OSM) and Deep Reinforcement Learning..

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3.2 Architecture

The architecture used to achieve the objectives is shown in Figure 6. The architecture used the ETSI MANO framework with the network functions simulated using Open5GS and the RAN part which acts as the Traffic Generator simulated using UERANISM. A DRL model has been introduced to work with the NFVO. The NFVO and VNFM are implemented using Tacker and VIM is implemented using OSM.

3.3. Reinforcement Learning Algorithm

The automation agent has been modelled as a Markov Decision process with the following sub-elements:

Goal:

• To get the best possible QoS by looking at throughput and delay.

Agent:

• The Deep Reinforcement Machine Learning algorithm.

State:

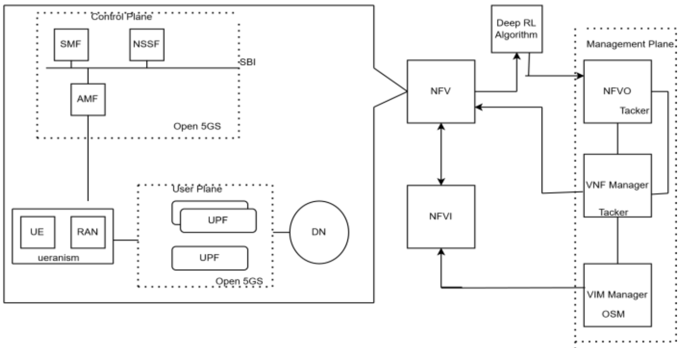

Figure. 6 Architecture Overview

- Throughput (To ensure the throughput is at least 90 percent)
- Delay: (To check on both delay and jitter and ensure variation in delay(jitter) does not exceed 20 ms) Actions:
- To increase the number of UPFs and do load balancing.
- To maintain the number of UPFs
- To increase the bandwidth of UPFs

Reward Components:

- Throughput: Maximize throughput by creating more slices with throughput above 90 percent viewed as a positive reward component and below 90 percent as a negative reward component
- Delay: Minimize delay by having reduced delay as a positive reward and penalize excessive delays
- load-balancing-promote load balancing of resources.
- Trade-off: This is to optimize the 2 main objectives and promote load-balancing and so scaling factors are introduced.

Reward function Design:

Reward = $\alpha * throughput - \beta * delay + \Gamma * load-balancing$ where

- α, β and γ are scaling factors
- Throughput is measured in bits per second.
- Delay is measured in milliseconds and denotes the average wait time.
- load-balancing used to quantify resource distribution.

The parameters are initialized by.

- Learning rate, α =0.9
- Discount factors, β, Γ = 0.99
- Exploration rate = 1.0

4. System Evaluation

The system was evaluated by defining throughput, jitter, and response times as the evaluation metric with the bandwidth as the cost. Throughput was measured before the traffic got into the UPF and measured after the traffic at UPF A Models For the sake of evaluation, three models were used.

1. Model with a single UPF with a bandwidth of 100 Mbps as shown in *figure 7*. This was used as the baseline model as it references unsliced networks.
2. Model with a single UPF but a higher bandwidth of 150 Mbps as shown in *figure 8*.
3. Model with two combined UPF (Each a bandwidth of 100 Mbps) with traffic load balanced between the two as shown in *figure 9*.
4. A model that had a Machine Learning Algorithm introduced to verify the automation.

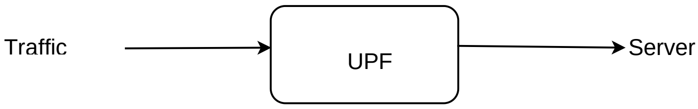

Figure. 7 Model with 100 Mbps bandwidth constraint

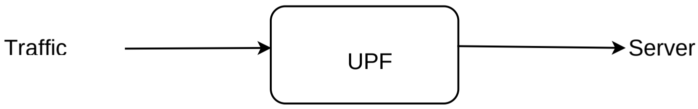

Figure. 8. Model with 150 Mbps bandwidth constraint

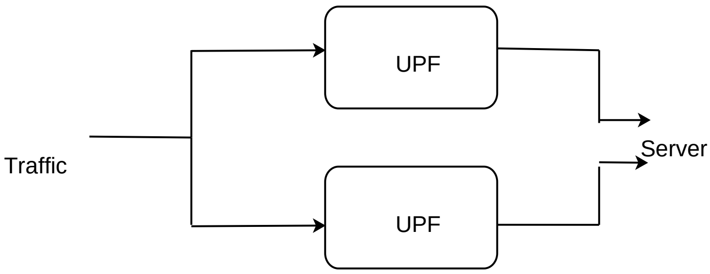

Figure. 9. Model that is load balanced between two UPF with 100 Mbps constraint

5. RESULTS AND DISCUSSION

For the simulation, UDP (User Datagram Protocol) was used to generate traffic. UERANISM was used to simulate the RAN part and it generated the same traffic type of 100 Mbps. UERANISM set up PDU sessions and then generated the packets with 100 Mbps. In comparison, the first model with a bandwidth constraint of 100 Mbps had a throughput of 78 Mbps. The model with a bandwidth constraint of 150 Mbps had an average throughput of 92 Mbps. The model with a load

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balancing capability had the highest throughput of 97 Mbps. *figure 10* compares the throughputs of the various models.

To check on the delay, ping was used, and the overall time taken from round trip delay was measured. The sliced load balanced model had the least time of 23.4 ms. The model with 150 Mbps bandwidth constraint had 35.5 ms and the model with 100Mbps had a 50ms. *Figure 11* compares the delays.

Bandwidth increase resulted in a reduction in delays and more throughput. However, with the same bandwidth sliced and the traffic load-balanced then the delay is reduced further, and aggregated throughput increases. A combined UPF with load-balancing capability has the best throughput and least delay. Bandwidth increase increased the throughput and reduced the delays due to more resources being available for the traffic. Slicing was able to reduce the delay due to packets taking different routes and therefore minimizing the resource contention. Load balancing capability also improves on the delay by ensuring all the slices are equally used and therefore more packets can be transported faster. The DRL machine learning algorithm was used to automate the process with the ability to combine UPFs to increase throughput in case it is declining by checking the throughput at the outlet of UPF and the throughput at the inlet of UPF and can dynamically add UPFs to compensate on QoS. The model that has both DRL and network slicing has a lot of benefits compared to unsliced modes as seen in *table 1*.

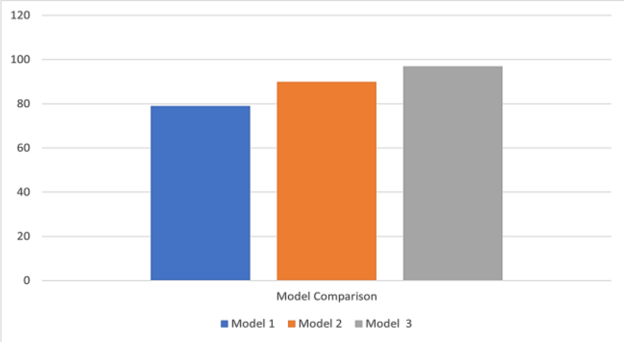

Figure. 10. Comparison in terms of throughput for various models

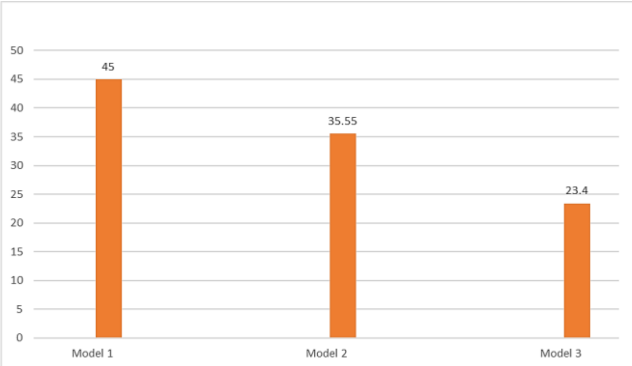

Figure. 11. Comparison in terms of delay for various models

Table 1: Comparison of Proposed DRL based sliced model and unsliced model

	Model with DRL and Network Slicing	Non-slicing Model
QoS Performance	Consistent quality of service since it can adapt to optimized QoS parameters (throughput and delay)	Since resources are allocated uniformly the QoS varies and thus impacts critical devices.
Resource Allocation	Dynamic allocation of resources has resulted in efficient use of resources.	Uniform resource allocation thus resulting in under-utilization of resources.
Dynamic adaptation	The dynamism in the allocation of resources by creating or removing UPFs makes it more efficient	Uniform resource allocation does not offer adaptability.
Intelligence	The model can be improved by gaining more intelligence from the data provided	The network does not improve in terms of intelligence.
Complexity	The model is more complex to design and requires a lot of data to achieve its full potential	The model is simpler to design.
Scalability	The model can accommodate more services easily by just creating more slices.	To add more services, more resources must be added to the network.

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6. CONCLUSION

Network slicing and load-balancing improve the QoS of the 5G network and the intelligence brought by Machine Learning models reduces remediation times for the QoS. However, the effects of slicing on jitter should be explored further to check how a trade-off with the number of UPFs can be achieved. The DRL algorithm should also be used.

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