DeepSlice: A Deep Learning Approach towards an Efficient and Reliable Network Slicing in 5G Networks

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***Abstract* – Existing cellular communications and the upcoming 5G mobile network requires meeting high-reliability standards, very low latency, higher capacity, more security, and high-speed user connectivity. Mobile operators are looking for a programmable solution that will allow them to accommodate multiple independent tenants on the same physical infrastructure and 5G networks allow for end-to-end network resource allocation using the concept of Network Slicing (NS). Data-driven decision making will be vital in future communication networks due to the traffic explosion and Artificial Intelligence (AI) will accelerate the 5G network performance. In this paper, we have developed a 'DeepSlice' model by implementing Deep Learning (DL) Neural Network to manage network load efficiency and network availability, utilizing in-network deep learning and prediction. We use available network Key Performance Indicators (KPIs) to train our model to analyze incoming traffic and predict the network slice for an unknown device type. Intelligent resource allocation allows us to use the available resources on existing network slices efficiently and offer load balancing. Our proposed DeepSlice model will be able to make smart decisions and select the most appropriate network slice, even in case of a network failure.**

Keywords – 5G Cellular Networks, Network Slicing, Machine Learning, Deep Learning Neural Networks, Network Slicing Optimization, Survivability of Network Functions.

I. Introduction

Mobile communication has become an essential part of human lives. The increase in the number of mobile devices has been exponential over the past two decades, where newer services and applications play the role of a catalyst. This change has not only led to a need for higher capacity and throughput in the network but requires close integration of multiple different technologies. However, seamless operations and management have always been a challenge for heterogeneous wireless networks, but many service providers have worked their way through to meet customer demands. The next generation 5G network is an expansion of the current LTE network and is revolutionizing the wireless industry by creating new business opportunities, opening doors for new services and bringing innovation. 5G networks are seen to be multi-service network with a wide range of operations embedding diverse performance and services which in turn calls for a broader device eco-system. They will enable richer mobile experience whether it's mobilizing media and entertainment, high-speed mobility, immersive experiences, augmented reality, connected vehicles in the congested network environment. Our work integrates Deep Learning mechanisms to understand traffic requirements and trends to make accurate decisions in 5G networks.

Many emerging technologies have taken ablaze the telecom industry by enabling new business models and providing customers a different experience. Networks have evolved with the introduction of programmable systems like the Software Defined Networks (SDN) and Network Function Virtualization (NFV) and have benefited ever since their implementation. Some critical services that 5G networks would encapsulate are autonomous driving, enterprise business models, AR-VR solutions, industrial automation, remote monitoring, smart health, smart cities, and many more. The Third Generation Partnership Project (3GPP) considers network slicing a key enabling technology for 5G. Slicing would allow operators to efficiently run multiple instances of the network over a single infrastructure for serving various applications, use cases, and business services with superior Quality of Service (QoS).

The main goals of our model are (1) appropriate selection of a network slice for a device, (2) correct slice prediction and allocating enough resources to that slice based on the traffic prediction, and (3) adaptation of slice assignments in cases of network failures. The key tools for accomplishing these goals are deep learning neural networks. This paper makes use of ML and Deep Learning Neural Networks (DLNN) to help make the most efficient and optimized selection of network slices for devices and/or services. Our DeepSlice model also analyzes the overall traffic pattern and can predict future traffic, so it can allocate resources, in advance, to the most appropriate slice.

The telecom industry is going through a massive digital transformation with the adoption of ML, AI, feedback-based automation and advanced analytics to handle the next generation applications and services. AI concepts are not new; the algorithms used by Machine Learning and Deep Learning are being currently implemented in various industries and technology verticals. With growing data and immense volume of information over 5G, the ability to predict data proactively, swiftly and with accuracy, is critically important. AI will enable network functions to deliver ultra-low latency, higher throughput, and reliability by optimizing network performance and improving Quality of Experience (QoE).

We briefly introduce 5G network slicing and deep learning concepts in Section II, some background work details are in Section III, we explain our DeepSlice model in Section IV and in Section V we present our results and discuss its application for our use cases of slice prediction for unknown device types, load balancing and network failover scenario. Finally, in Section VI we conclude our work and propose possible future extension.

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II. 5G Network Slicing, Machine Learning And Deep Learning

The current LTE architecture has a rigid framework that is not very flexible or scalable to adapt to diverse use cases. It often lacks customization when it comes to offering any tailored business requirements or to meet specific business demands. With growing mobile data and consumer demands, business needs for faster connectivity and higher throughput cannot be fulfilled by today's 4G LTE network. Network slicing in 5G can cost-effectively deliver multiple logical networks over the same physical infrastructure. SDN and NFV together would allow us to manipulate these slices as and when needed without having to touch multiple different physical equipment in the network. Almost 'no-disruption' to any existing services is possible. Currently, service providers must configure and stitch together several components and equipment to achieve network slicing in 4G. Use of Access Point Name (APN) or Public Land Mobile Network (PLMN ID) are examples that service providers implement today for Mobile Virtual Network Operator (MVNOs), enterprise customers, etc. There is a lot of work done on optimization and efficient scheduling of radio and network resources; however, application or service-based resource allocation is a necessity and a must-have feature in 5G networks.

Operators have a huge amount of data traffic coming through their network which will increase with growing number of devices and additional services of 5G networks. This traffic can be segmented and dealt with individually and independently. It will benefit any service provider as they can now charge differently for each sliced segment and even adjust the cost for each slice, leading to a balance between business profitability and customer satisfaction. In addition, 5G network slicing allows service providers to build for all current use cases that have been around for a while, and some emerging applications and services as well. It will provide a 'one size fits all' approach. Each network slice can be isolated, have individual control and policy management systems. The inclusion of ML here will allow us to analyze any unknowns and take necessary corrective actions. ML will provide network analysis of the huge data which can be studied further to efficiently and cost effectively modify any given slice as needed. DL for instance, as represented in Fig. 1, can trigger automation in the network to modify available resources and make changes on the go. DL will be responsible not only to provide and process, but also make an intelligent decision for network resource adaptation without any human intervention. It will also combine a variety of factors to make the best decisions, possibly too many factors for a human to consider at once or even be able to process in a short time.

DL will perform real-time analysis for any given slice to determine the network performance, create a potential baseline for performance, be proactive in anticipating problems, inspect different network elements, and find out if anything is abnormal. A simple example could be on a slice for fixed wireless enterprise network, wherein if the network sees a sudden demand increase, automation can add more capacity in real time to provide efficient communication. This will help to create any newly required services or slices in the network. Automation will facilitate all this in a shorter timespan without causing any performance issues to an on-going session. Current hurdles in implementation of network slicing are organizational, as one will have to touch several different pieces of hardware and groups in a service provider network, to make a single change. The programmability capabilities of 5G will provide flexibility to seamlessly stitch together an end-to-end service for any application. A typical consumer would request parameters like data rate, latency, mobility, isolation, power constraints, etc. Accordingly, a specific network slice type is provisioned if the existing network slice instance does not have enough capacity and associated network functions are initiated on demand.

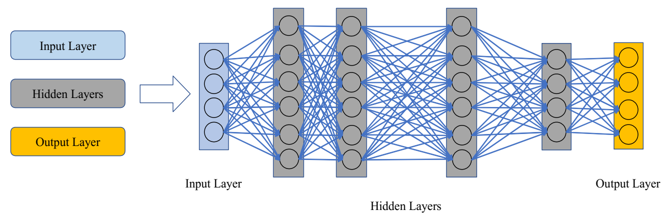

Figure 1. General Deep Learning Neural Network

Each use case receives an optimized set of resources in the network topology covering several SLA specified factors like connectivity, latency, priority, service availability, speed, capacity, etc. that suit the need of an application. The key parameters that are determined for network slicing are the slice type, bandwidth, throughput, latency, equipment type, mobility, reliability, isolation, power, etc. 5G enables enormous amounts of data collection, and this leads to the need of ML for big data analytics. Some of the most relevant and useful ML-based applications in the wireless industry are identifying and restarting sleeping cellular cells, optimizing mobile tower operations, faster wireless channel adoption, facilitating targeted marketing, autonomous decision making in IoT networks, real-time data analysis, predictive maintenance, customer churn, sentiment analysis by social networking, fraud detection, e-commerce, etc. ML implementation in Uber-like applications will have many advantages since Uber follows differential pricing in real time based on the demand, cars available, weather conditions, rush hour, etc. and so ML-based platform will allow for better accuracy and future prediction based on enormous data from the past and in the present.

III. Related Work

Authors in [1] explore the multi-tenancy nature of the 5G network slicing by demonstrating how the capacity of a MVNO is affected by the number of users, transmit power. SDN and NFV-based 5G core network architecture is defined in [2]. Ping and Akihiro propose an application-specific mobile network deep learning architecture to apply application specific radio spectrum scheduling in the RAN [3]. Authors in [4] propose a framework to prioritize network traffic for smart cities using a priority management SDN approach. Taewhan started work early on network slicing and discusses standardization of network slicing, network slice selection, identifying slice-independent functions and then proposes an architecture for slicing and the RRC frame [5].

Other than this work, no other work to our knowledge considers the easily overlooked but difficult problem of deciding which devices and connections should be assigned to which network slices. And our work here is the first to use deep learning to address this problem, which will provide benefits of fast, flexible, accurate and informative decision making in the process. The authors in [6] contrasts Fade Duration Outage Probability (FDOP) based handover requirements with the traditional SINR based handovers methods in cellular systems. Another SDN and NFV based work on slicing demonstrates dynamic data rate allocation and the ability to provide hard service guarantees on 5G new radio air interfaces [7]. Many industry white papers and network surveys have been published and an Ericsson mobility report predicts the growth of mobile devices, 5G network connections and the overall data usage in coming years [8]. As for network intelligence, the authors in [9] represented handovers using matrix exponential distributions for public safety and emergency communications, which helps make handover decisions more accurate considering all the different parameters involved in the decision process.

Authors in [10] present network survivability framework in 5G networks demonstrating network virtualization with multiple providers which necessitates network slicing in 5G. Virtualized networks or slices of virtualized networks are selected and assigned based on QCI and security requirements associated with a requested service in [11]. Campolo, et. al., share their vision about V2X network slicing by pin-pointing key requirements and providing a set of design guidelines, aligned with ongoing 3GPP standard specifications and network softwarization directions in [12]. The proposed model in [13] enables a cost-optimal deployment of network slices allowing a mobile network operator to efficiently allocate the underlying layer resources according to its users' requirements. However, none of their work considers the possibility of multiple service requirements requested by the same device, especially requested by an unknow device. Also, network slice load balancing and future prediction of traffic is unique in our work, especially with the use of ML and DL neural networks.

IV. Proposed System Model – 'DeepSlice'

Neural networks are widely used in the industry today, and their usage will only grow as the ever-growing devices on 5G networks generate massive data. Accurate analysis and decision making will be overwhelming for any human being and faster processing times are required. We first create an ML model and later build a DLNN to help decide which network slice to use for given input information. The developed 'DeepSlice' is then used to manage network load, slice failure conditions and detect the most appropriate slice for any new unknown device type connecting to the network. A statistical ML model is based on the Random Forest (RF) algorithm, and the DeepSlice uses a convolutional neural network (CNN) classifier. Both RF and CNN are widely used models in their respective domains. We use the exact same dataset for both our ML and DLNN models consisting of over 65,000 unique input combinations.

Our dataset includes most relevant KPIs from both the network and the devices, including the type of device used to connect (Smartphone, IoT device, URLLC device, etc.), User Equipment (UE) category, QoS Class Identifier (QCI), packet delay budget, maximum packet loss, time and day of the week, etc. These KPIs can be captured from control packets between the UE and network. Since our model will run internally on the network, all this information is readily available. We have multiple different types of input devices requesting access to our system. As shown in Fig. 2, these include smartphones, general IoT devices, AR-VR devices, Industry 4.0 traffic, e911 or public safety communication, healthcare, smart city or smart homes traffic, etc. or even an unknown device requesting access to one or multiple services. These have UE category values defined to them and the network also allocates a pre-defined QCI value to each service request. In 5G, the packet delay budget and the packet loss rate are an integral part of the 5QI (5G QoS Identifier), and we have them included in our model. DeepSlice will also observe what time and day of the week is the request received in the system. All this information will be recorded and used by our DLNN to make smart decisions in the present and efficiently predict network resource reservation for the future.

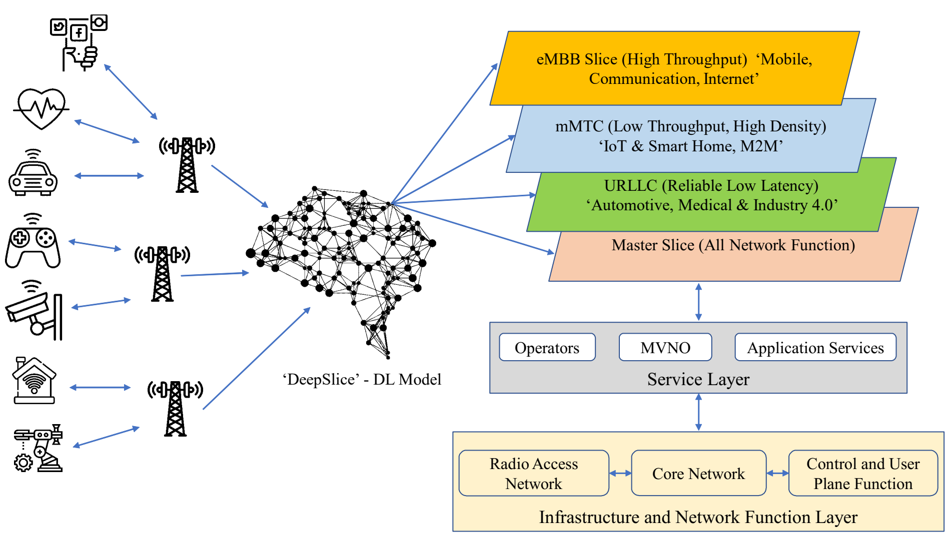

Figure 2. General representation of our Deep Learning Neural Network Model 'DeepSlice' consisting of Network Slices

Input Type	Duration (sec)	Packet Loss Rate	Packet Delay Budget (ms)	Predicted Slice
Smartphone	300	10^{-2}/10^{-3}/ 10^{-6}	60/75/100/ 150/300	eMBB
IoT Devices	60	10^{-2}	50/300	mMTC
Smart Transportation	60	10^{-6}	10	URLLC
Industry 4.0	180	10^{-3}/10^{-6}	10/50	mMTC/URLLC
AR / VR / Gaming	600	10^{-3}	10/50	eMBB
Healthcare	180	10^{-6}	10	URLLC
Public Safety / E911	300	10^{-6}	10	URLLC
Smart City / Home	120	10^{-2}	50/300	mMTC
Unknown Device Type	60/120/ 180/300	10^{-2}/10^{-3}/ 10^{-6}	10/50/60/75/ 100/150/300	eMBB/mMTC/ URLLC

Table I. Feature highlights of our DeepSlice simulation model

In Table I, we have shown highlights of the features of our simulation model. The second column shows the average time duration spent in the system by each of the incoming requests. All these incoming requests are directed to one or more of the network slices as predicted. We have also considered some variations in the traffic types; mMTC devices can be further categorized as ones requiring a continuous connection link and others needing only a momentary connection to send data periodically. Smartphone devices can be used by common users to make phone calls, browse the web and at the same time by first responders in an emergency (lower packet loss and packet delay). Our pre-defined slice categories include enhanced Mobile Broad Band (eMBB), Ultra Reliable Low Latency Communication (URLLC), massive Machine Type Communication (mMTC) and the Master slice. The Master slice is the slice that will have network functions belonging to each of the other slices. It can always act as a back-up slice, in a hot-standby, and will be used depending on the load on other slices.

In our proposed model, we predict the network load on each network slice based on the previous information of incoming connections and keep track of which output 'network slice' is being utilized the most. We then allocate incoming traffic to the network by efficiently distributing them between all the slices as desired. We have used Keras which is a deep learning library in Python for our model simulations. A DLNN is required as there are no clear sets of rules for how each incoming device type should be treated. Cellular handovers, for example, are based upon several network factors. With every new scenario, an intelligent network can learn and adapt very quickly to changes or new requirements compared to traditional algorithms. DLNN can help identify and accommodate the unknows in the network.

A. *Machine Learning with Random Forest Algorithm*

When we have a well-structured data with multiple attributes, use of Random Forest (RF) along with DLNN is the most recommended option. RF is a supervised learning model and mainly used to build predictive models for both classification and regression problems. The main reason for selecting RF for our model over k-Nearest Neighbor, Naive Bayes, or Decision Tree is simply because of the nature and amount of data we have in our dataset. We have around 65K unique inputs, and all this data is well structured, so RF reduces the risk of overfitting by using multiple sub-trees. RF is useful to quickly classify input data into any pre-defined category. RF runs efficiently on a large database and produces accurate predictions. Most importantly, it estimates any missing data and maintains the accuracy even when some input data is missing.

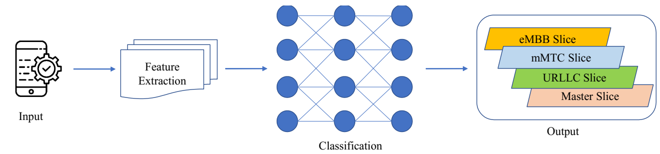

Figure 3a. Machine Learning Model

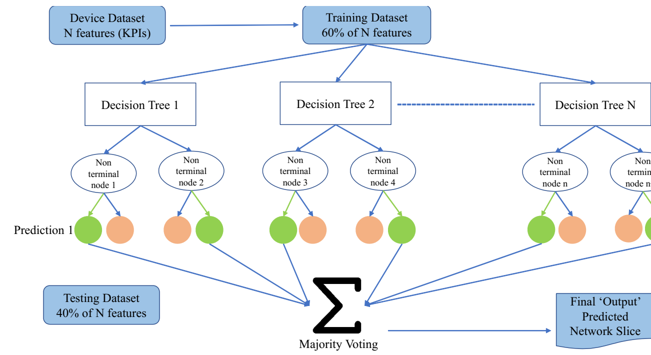

Figure 3b. Random Forest Decision Tree based ML Model

Figs. 3a and 3b illustrate the typical ML modeling with decision trees and predicting the output with majority voting. As per our input dataset, we have about 8 different input strings that will together contribute towards a decision that the model will make. And it can very well happen in the real-world scenario that one or more among the 8 inputs may not be received and our model still must predict an output. During training of our data, RF constructs multiple decision trees based on inputs, each branch of a tree represents a possible occurrence or response. We use 70% of our input dataset to train our model and the remaining 30% was used for predicting the classifier accuracy. The RF algorithm in our ML model gives high accuracy.

B. *Deep Learning Neural Network*

The DLNN works best when the data is unstructured and huge. We use the same dataset to train multiple neurons of our DLNN, and it predicts the correct network slice based on any input from the UE information. Our DLNN can predict very accurately and we utilize this functionality to select the correct slice for unknown device types. It helps redirect traffic to the Master slice if load balancing is required in the network slices, and in case of any slice failure in the network. In our proposed DeepSlice model in Fig. 4a, we predict the network load of each network slice based on the incoming connection and keep track of which output 'network slice' is being utilized most. We then allocate incoming devices to slices by efficiently distributing between the eMBB, URLLC, mMTC or the master slice depending on the load and the output predicted by our model.

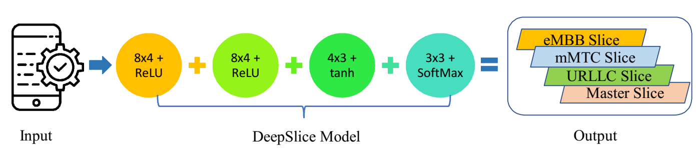

Figure 4a. 'DeepSlice' DLNN Model Overview

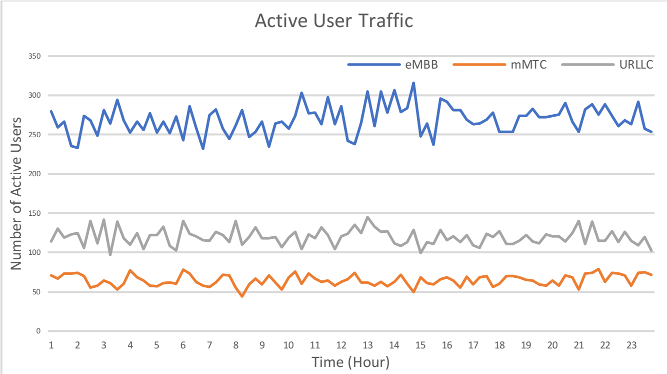

Figure 4b. Active user count in the network observed every 15 minutes

Approximately a quarter million user connection requests were generated in a 24-hour simulation of which 40% was eMBB, 25% mMTC and 35% URLLC. Fig. 4b above shows the simulated DLNN model run for 24 hours giving the number of users being served at an instance. The plot begins when our model had reached a steady state which was at the 1-hour mark. Based on the Table I information, all incoming traffic has a pre-defined time-to-live (TTL) and so only a fraction remains alive every second. For example, eMBB active user average count was 275 at any given instance. URLLC and mMTC users were allotted short TTL compared to the eMBB which is why we have more users alive for broadband services. This can help analyze the user pattern and will allow for automated decisions based on the retrieved input information from the connected device.

DeepSlice will eventually learn and understand what kind of a device goes to what slice and it will evolve over time to be able to predict future connections requiring a specific service or a network slice. It can help prepare the network for any new connections by properly allocating resources in advance; this will save any delays later. Our dataset includes day and time of any connection which can also help the network predict number of connections in the future at any given time and would be aware what network slices would be required or requested by those connections based on learning from the past information.

V. Use Cases And Performance Evaluation

In this section, we evaluate DeepSlice and verify how it can be used to provide slice prediction, load balancing and network availability. In our first use case, we validate our approach by demonstrating how slices are accurately selected for any unknown device types requesting connections to the system. Our second use case of load balancing involves efficient utilization of each of the available network slices. If any individual slice utilization exceeds a certain threshold of its total available resources, our model will direct any new connections to the master slice that is otherwise required to carry the device when a slice utilization exceeds a pre-defined threshold. Our third use case depicts a slice failure scenario where all that traffic will route to the master slice instead and prevent any loss of service during failure of the slice. DeepSlice will capture the time of any connection failure and some attributes around the failure; the next time it can try to isolate the issue and be prepared in advance.

A. *Unknown Device Type*

DeepSlice model is trained using our dataset of multiple unique inputs based on network and device KPIs. Our cross-validation accuracy was over 90.62% (Fig. 7a) which included the entire test dataset of new input scenarios, those not used while training. We also included certain unknown device types with randomly selected parameters. Slice prediction accuracy was 95% for unknown devices. Table II shows a few unknowns and how only a portion of input information was used to correctly determine the network slice to be used.

Input Type	Technology	Packet Loss Rate	Packet Delay Budget (ms)	Predicted Slice
Unknown – 1	LTE/5G or IoT	10^{-3}	50	eMBB/mMTC
Unknown – 2	IoT	10^{-2}	50	mMTC
Unknown – 3	IoT	10^{-6}	10	URLLC
Unknown – 4	IoT	10^{-2}	300	mMTC
Unknown – 5	LTE/5G	10^{-2}	100	eMBB
Unknown – 6	LTE/5G	10^{-6}	100	eMBB

Table II. Slice prediction for unknown device types

Our training dataset included 6 to 8 parameters in every input, but our model requires a minimum of 2 or 3 input KPIs, to determine the services requested and allocate the correct slice. This is very essential, since a lot of devices with various capabilities request different services at different times. An industry 4.0 IoT application requires very low latency in pharmaceutical environments (URLLC), whereas the same type could also be used for monitoring production lines, which would require periodic connection and very low throughput (mMTC).

B. *Load Balancing Scenario*

We use the same DLNN but assume that one slice would be overutilized if the number of connections exceed a threshold, say 90% usage in our case. Fig. 5a shows an eMBB slice is detected to have over 90% utilization with its traffic to go over the set threshold, so, the master slice acts as backup for any new eMBB connections. Our DeepSlice can realize this overload and can be prepared next time to redirect traffic without causing one specific slice to be overloaded. When compared with Fig. 4b, the master slice takes over the excess traffic as shown in Fig. 5b.

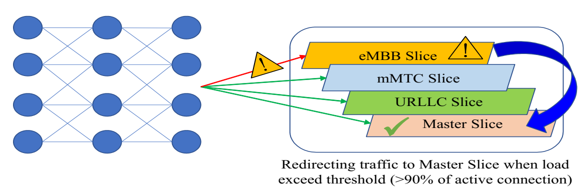

Figure 5a. Slice Utilization exceeding a pre-defined threshold

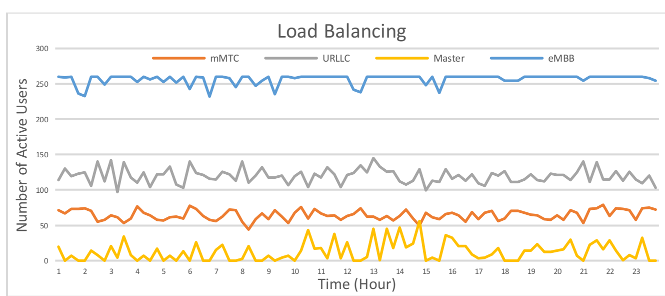

Figure 5b. Slice Utilization exceeding a pre-defined threshold

C. Network Slice Failure Scenario

In this case, we assume a complete failure of a specific slice, specifically eMBB as shown in Fig. 6a. Now the DeepSlice will direct all new eMBB related traffic to the master slice and avoid any loss of traffic transmission in the network. However, any ongoing communication on that slice would be impacted and all existing connections are lost due to sudden slice failure. This is recorded by the system, say for example, date and time, and care will be taken next time to avoid loss of all ongoing connections. Fig. 6b shows that our simulated model had failures on the mMTC slice for a period of two hours from 3hr to 5hr and on the eMBB slice for another two-hour period 16hr to 18hr. The master slice was identified as a backup and used to redirect this traffic during those slice failures. We had substantial resources reserved in the master slice for each of our network slices in terms of capacity and processing speed.

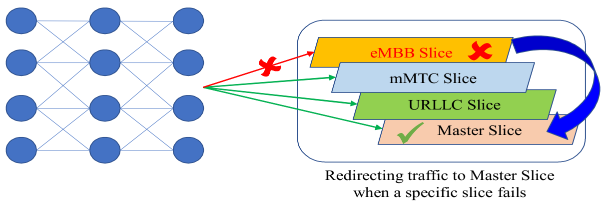

Figure 6a. Network slice failure and re-direction to master slice

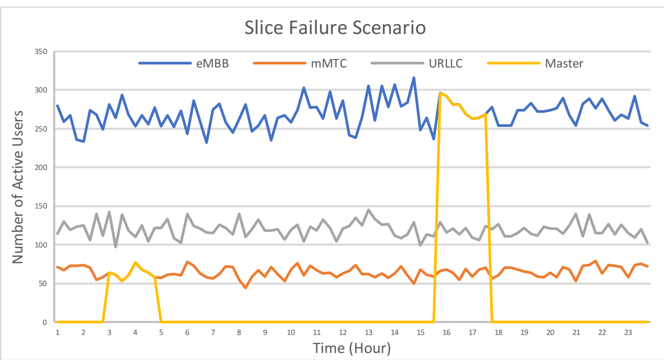

Figure 6b. Network slice failure and re-direction to master slice

We have run our simulation for a period of a day and later for a whole one-week period to get close to real-time results. The randomly distributed average connections received in an hour did not change between a day and a week. One-week simulation produced almost two million service requests. We also used multiple unknow device types and our model was able to maintain the accuracy for prediction of slices. Figs. 7a and 7b shows the accuracy or measure prediction quality of our model.

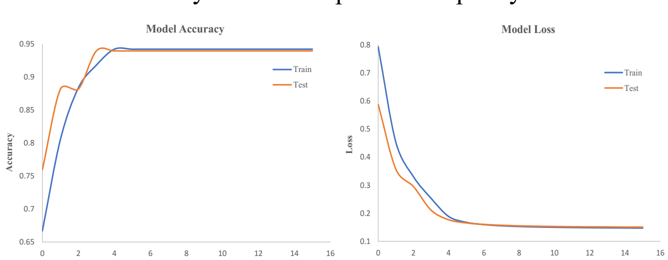

Figure 7a and 7b. Training and validation Accuracy and Loss

VI. Conclusion And Future Work

Network slicing in 5G is a critical feature for next generation wireless networks, mobile operators and businesses. We have demonstrated the benefits of using DeepSlice for accurately predicting the best network slice based on device key parameters and orchestrated the handling of network load balancing and network slice failure using neural network models. Our future work will include emulating the developed model in a real production environment once the 5G ecosystem with devices and networks are commercially available for consumers. We will also extend and further improve this model to handle scenarios such as handovers, caching and predicting the future load, borrowing resources from other slices, and application-based slice management use cases.

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