UNIVERSITY OF DAR ES SALAAM

COLLEGE OF INFORMATION AND COMMUNICATION TECHNOLOGIES (CoICT)

DEPARTMENT OF ELECTRONICS AND TELECOMMUNICATIONS ENGINEERING (ETE)

TE 499: FINAL YEAR PROJECT REPORT

IP NETWORKS QoS OPTIMIZATION USING ML POWERED SDN

THE CASE STUDY OF UDSM LAN

A Project Report in Partial Fulfillment of the Requirements
for the Award of Bachelor of Science in
Telecommunications Engineering

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Submission Date:	August 13, 2020

Declaration of Authorship and Originality

I, **SAMSON, Emmanuel Julius**, with registration number **2016-04-01802**, declare that this report and the work described in it are my own work, with any contributions from others expressly acknowledged and/or cited.

I declare that the work in this report was carried out in accordance with the regulations of the university of Dar es Salaam and has not been presented to any other University for examination either in Tanzania or Overseas. Any views expressed in this report are those of the author and in no way represent those of the University of Dar es Salaam.

SIGNED: .....
DATE: August 13, 2020

This report may proceed for submission for assessment for the award of B.Sc. in Telecommunications Engineering at the University of Dar es Salaam.

Supervisor's Signature: .....
Date: .....

Abstract

The fourth industrial revolution has brought about invaluable developments both in the way the information is shared within localities and around the world. The Internet is the tool that is powering this revolution. The academic institutions have not been left out in adopting the uses of the Internet and developing necessary algorithms for enhancing resources sharing around the globe.

The work herein employed UDSM LAN to address and provide solution to varying QoS experienced by the users using the same network but at different sub-networks. Bandwidth being one of the ways that QoS can be addressed, it was the focus of this work to develop a mechanism which would allow for dynamic bandwidth allocation depending on the relative amount of traffic flowing in different sub-networks of the same network. Hence, addressing the solution to static bandwidth allocation that leaves a loophole for under-utilization of resources at one sub-network while others may be experiencing congestion.

To do that, an IP traffic data generator was developed, taking into consideration the stochastic nature of the number of packets per flow and the mean of the delays associated with such flows. It was used to generate the data that was used during this work. Thereafter, the IP traffic data prediction algorithm—which considers the past traffic data points as the determinants of future traffic—was developed using the concepts behind poisson regression in order to address the stochastic nature associated with the generated data.

Using the mathematical model obtained after running several tests, the bandwidth allocation algorithm employed the mean of the predictions at one sub-network as the determinant for allocation against the sum of all means from all the sub-nets in the network.

The report herein introduces the problem in chapter 1, then discusses different literature in chapter 2. Chapter 3 discusses the methodology while chapters 4 and 5 discuss the data analysis, algorithm development and design considerations. Conclusions are drawn in chapter 6.

Acknowledgement

First and foremost, the life we have and the moments we are sharing are simply the gift from the Almighty God without whom this work would have never been possible to complete. It is, therefore, with gratitude that I thank him for all the grace, energy and purpose he has granted me with.

My family has been so much supportive during my Academic journey. Now that this has come to an end, I take this opportunity to thank them for their involvement and support, inclusiveness and compassion and at most times unceasing encouragement during my stay at the University. Special thanks to my Mom, Ms. Adelina Kajubu, and my brother, Dr. Charles Nyaitara.

The Vi Team I have been around with from the First year has been very helping. Sincerely, it is due to the long nights we had together, short days we shared and unwavering support we freely granted to one another that motivated me for this work at first. The challenges that we always posed to one another and silent geeks within everyone in the team are the ones that not only made this work possible but also other works of the like. The future holds great things for this team.

Dr. Prosper Mafole has been one of the best teachers I have ever had. Apart from being a teacher, he has been able to act as a Mentor and an Advisor without crossing any of the lines whenever the situations changed. He has been an inspiration and a great living legacy. His commitment, and hard work would never have left anyone working with him relaxed. Therefore, it is with great respect that I honor him. This work should be one of those he can stand up there with and say, ”The DIY principle isn’t just words. It can be done; it has been done; and it will be done by anyone who puts their heart to it.”

Lastly, I appreciate everyone who participated in this work either directly or indirectly. Their comments, challenges, corrections and every other piece of information provided have been invaluable. Special appreciation to the community around CoICT for the brains they put into use are one of the greatest assets and one that they do not just let rest and settle for small achievements.

Table of Contents

List of Acronyms and Abbreviations

API	Application Programming Interface
ATM	Asynchronous Transfer Mode
BW	Bandwidth
DPI	Deep Packet Inspection
Gbps	Gigabits per Second
GPS	Generalized Processor Sharing
GR	Guaranteed Rate
ICT	Information and Communication Technologies
IETF	Internet Engineering Task Force
IP	Internet Protocol
Mbps	Megabits per second
ML	Machine Learning
NN	Neural Networks
QoE	Quality of Experience
QoS	Quality of Service
RFC	Request for Comments
SDN	Software Defined Networking
SNMP	Simple Network Management Protocol
SNMPvx	SNMP Version x
STM-x	Synchronous Transport Module level-x
TCP	Transmission Control Protocol
TSF	Time Series Forecasting
UDP	User Datagram Protocol

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Chapter 1

Introduction

1.1 Introduction

Internet has been the very important technology since its release for the educational research community earlier and later for the general public in 1983 [3]. It first began with the simple file sharing amongst ARPANET computers. Since its adoption and its release to the whole world, Internet has proved to be an essential part and parcel of all activities in the world. Information sharing, online businesses, social networks, and education materials delivery (a few of the many value added services) happen due to enhanced connectivity around the world. The Internet has made it possible to find or deliver or search for or share information, make transactions, and so many others, in just a matter of seconds or at most a minute.

Like any other institutions out there, the University of Dar es Salaam (UDSM) has made its efforts to make sure that the colleges, school, and institutions within it are connected to the outside world via the Internet. However, the quality of experience for the individual users of the network using wired and wireless means around the university to access the Internet are varying from time to time. Some colleges and schools experience slow Internet connections while some other colleges experience faster connections. CoICT, for example, experiences very slow Internet connections during the day while SoED experiences the opposite. Nevertheless, the Internet connection speed at CoICT is always at its peak during night hours.

While it is true that the number of Internet service users affects the speed with which the individual users in a certain subnet access the Internet, and that it is deemed necessary to provide each subnet (in this case college LANs) with estimated needed bandwidth, it remains necessary to find the way that we can share the bandwidth that does not get used in other subnets during the times of congestion in one or more of them. It was, therefore, the focus of this work to devise the method that would optimize the allocated bandwidth in the subnet with respect to traffic in the other subnets.

Using the mathematical model obtained after running several tests, the bandwidth allocation

algorithm was developed. It employs the mean of the predictions at one sub-network as the determinant for bandwidth allocation against the sum of all means from all the sub-nets in the network. This ensures that the bandwidth is allocated at the sub-nets with respect to what is needed at the moment.

1.2 Challenges in Bandwidth Management

The need for a faster Internet connection remains pure. It proves even much more important when the study involves the academic institutions. Therefore, it was deemed necessary to look for the possible causes of a slow Internet connection from the experiences of other people. As mentioned in [4], below are bandwidth challenges faced by the Internet operators around the globe:

(i) Constant or increasing rates of traffic growth are commonplace – growth that is not always visible from publicly available sources.

(ii) We can't build infinite bandwidth to the edge everywhere. It is therefore necessary to engineer and deploy mechanisms that allow performance to degrade much more gracefully than is typically the case today.

(iii) Better architectural support for technical collaboration between network and content aggregators and application providers to deliver more network and application management data is a high priority.

However, the causes of the bandwidth instabilities and degradation of the QoS within the UDSM LAN have been analyzed and summarized to the following:

(i) Online video streaming during daytime.

(ii) Concurrent downloads of ultimate huge files during daytime.

(iii) Network elements misconfigurations—these lead to unavailability of Internet at times.

(iv) Absence of monitoring tools for each entity at the University to monitor their infrastructures internally. Hence, the means for dynamic allocation of bandwidth remains necessary.

1.3 How Challenges in Bandwidth Management are Tackled

Due to highlighted concerns for the improved Quality of Service of the UDSM LAN, different measures have been implemented including:

(i) Blocking of some sites that are known to consume much more bandwidth when the data traffic to the sites are allowed, e.g. most torrent sites.

(ii) Prioritization of traffic during very important events—particularly meetings—which trades the bandwidth sharing purposes to serving one particular event at certain times.

(iii) The use of passive network in providing effective solution to bottleneck problem [5].

(iv) The use of traffic shapers in the network.

Items (i) and (ii) above are both static approaches while (iii) is one case of dynamic solution.

1.4 Statement of the Problem

The reliability of the Internet remains an important factor for making sure that the activities around the university go on. Nowadays, most academic activities require that the students and instructors be connected to the Internet. Due to that requirement, a slow network would never serve the purpose. Neither would the fast network at maximum utilization or overutilization. Therefore, to ensure that the available bandwidth gets well utilized, and serves the connected institutions, with relatively the same quality of service to individual users without experiencing delays and jitters in accessing the services remains the question that needs immediate answers.

This work aimed at answering that question and propose the solution. Specifically, this study discusses the potential of employing machine learning in forecasting the future Internet traffic values from specific subnets so that the bandwidth can be allocated dynamically according to the demands of the institution at certain instances of time. On top of that, this study aimed at proposing a feasible and deployable operational architecture of the solution.

1.5 Motivation

To experience a better Internet connection, one must be able to appreciate the speed with which the information comes to them. However, varying levels of services between two or more

subscribers that are clients of the same service provider will definitely lead to dissatisfaction—which is exactly what is happening with CoICT. So, improving the QoS in the UDSM LAN would not only save a lot of bandwidth that does not get utilized but also improve the quality of experience from the users at highly congested areas.

It is that concern and the exploration of the possible available solutions to bandwidth sharing challenges that motivated me to explore the science and mathematics behind bandwidth allocation and management, especially in a shared environment.

1.6 Project Objectives

1.6.1 Main Objective

To address and provide solution to varying QoS experienced at different locations of the UDSM and propose a generalized solution for use in similar environments.

1.6.2 Specific Objectives

(i) To study the past traffic data at the UDSM LAN.

(ii) To develop a dynamic bandwidth sharing mathematical model.

(iii) To develop a bandwidth optimization algorithm.

(iv) To emulate the current UDSM network and test the developed algorithm.

(v) To propose the architecture that would support the operation of the model and the algorithm.

Chapter 2

Literature Review

2.1 Definition of Terms

(i) **IP Networks**

Considering the TCP/IP model, Figure 2.1, the Internet Protocol (IP) is one of the components on layer 3 of this layered architecture. It is responsible for relaying datagrams across network boundaries. Its routing functions enables internetworking and essentially establishes the Internet.

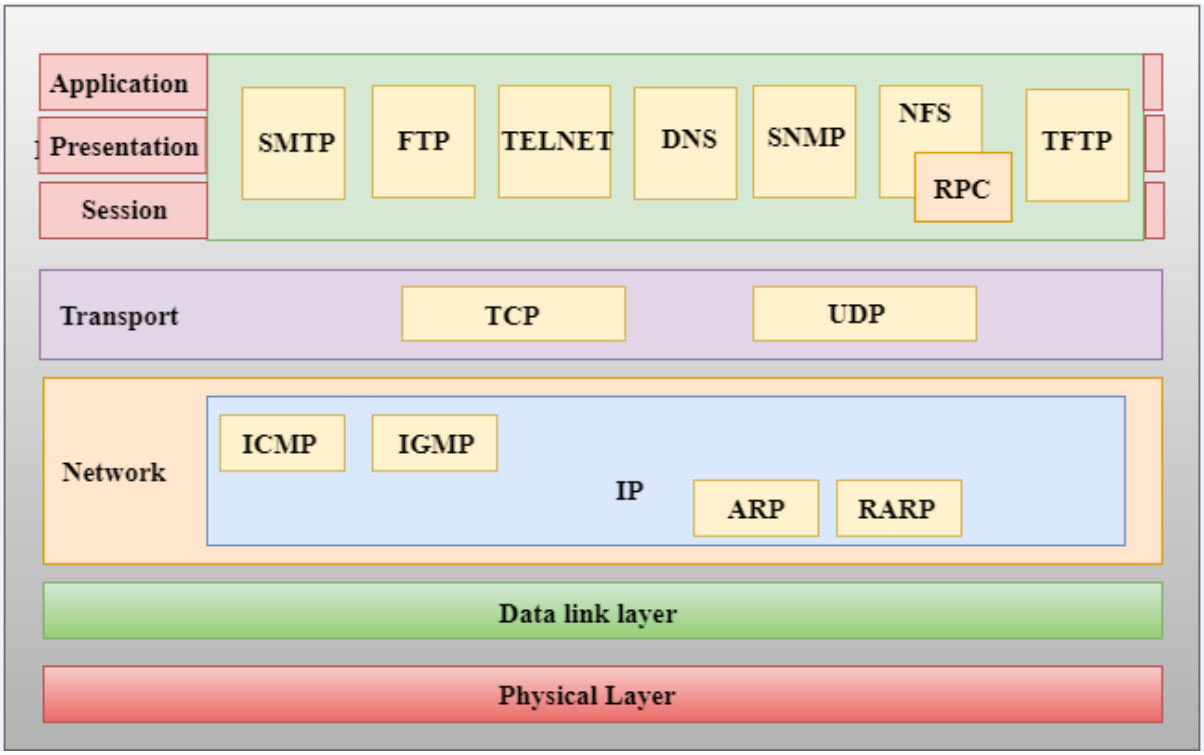

Figure 2.1: TCP/IP Model [1]

(ii) **Quality of Service**

The definition of QoS depends on the perspective adopted [6]. Considering the IP networks, QoS can be looked at from three main points of view namely:

(i) Packet drop probability

(ii) Delays

(iii) Delay Jitters

Therefore, with respect to the context of this work, QoS is defined as the probability of packet drop in the network. That is, the percentage loss of packets. This definition is adopted due to its close relationship with the bandwidth allocated for data sharing in the network. Narrow bandwidth would mean a limited number of packets flowing in and out the central router, hence resulting to congestion, higher latency levels and higher packet drop probabilities during peak times.

(iii) **Machine Learning**

Machine Learning (ML) is the scientific study of algorithms and statistical models that computer systems use to perform a specific task without explicitly being programed to [7, 8]. Machine learning falls into two categories: supervised learning, and unsupervised learning. Supervised learning involves providing the computer program with the past data that has certain inputs with some outputs (labels). The provided data helps the computer program to determine the meaning of the data. On the other hand, unsupervised learning utilizes the provision of the data without any labels and therefore has much more work to finding out what the data means. To do this, unsupervised learning uses certain number of algorithms including K-Means algorithm.

Considering the nature of the problem for the study centered at how past traffic was at the UDSM LAN, a number of supervised learning models could be used.

(iv) **Network Calculus**

This is a theory of deterministic queuing systems found in computer networks [9]. It is a set of recent developments that provide deep insights into flow problems encountered in networking. The foundation of network calculus lies in the mathematical theory of dioids, and in particular, the Min-Plus dioid (also called the Min-Plus algebra) [9]. With network calculus, we are able to understand some fundamental properties of integrated services networks, window flow control, scheduling and buffer or delay dimensioning. It presents the statistical network calculus in a setting where both arrivals and service are specified in terms of probabilistic bounds [10].

When a node performs a reservation, it is necessary to check whether local resources are sufficient. In general, the method for this consists in breaking the node down into a network of building blocks such as schedulers, shapers, and delay elements. Generally, network calculus considers the arrival and service curves in determining the required level of resources allocation for specific sessions. It considers the probabilistic arrival rates and develops the necessary models for optimization of the allocation of the service sessions in the routers.

According to [10], to exploit statistical multiplexing gain of traffic resources in a network, service provisioning requires a framework for the stochastic analysis of network traffic and commonly- used scheduling algorithms. The most influential such framework is the effective bandwidth which, from a qualitative point of view, describes the minimum bandwidth required to provide an expected service for a given amount of traffic [10]. However, applications of the effective bandwidth approach have generally been limited to large buffer asymptotes and other asymptotic approximations.

(v) **Software-defined Networking (SDN)**

While the fundamentals of network engineering rely on the traditional approach for the design, deployment and management where the forwarding, control and data planes are all embedded in one hardware [11], the networks are growing big and it becomes hard to manage each and every component of the network elements. SDN, however, brings about the separation between the three planes (Figure 2.2). At the control plane, that is where most of the configurations, network programmability and management take place. The data plane is responsible for handling the user traffic.

It is the easiness associated with the architecture that makes it fine for the networks that are prone to growing big over time to adopt the technique.

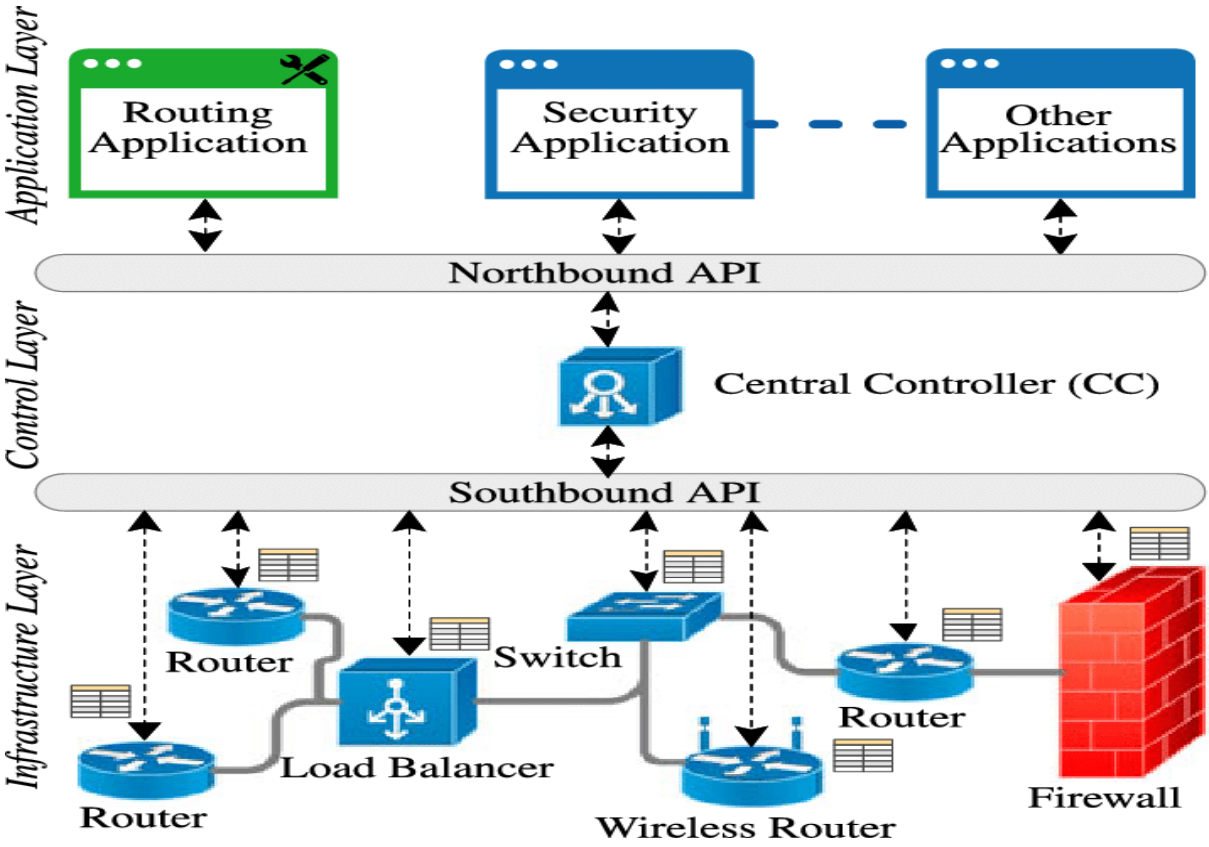

Figure 2.2: Software-defined Networking Architecture [2]

2.2 Current situation

Table 2.1 shows how the bandwidth was allocated with UDSM LAN at the beginning of this project.

Subnet	**Bandwidth Allocated (Mbps)** (Download/Upload)	**Burst (Mbps)**
Maths	32/32	35
Lib	5/5	10
CoET	20/20	25
Hall5	10/8	16/8
CoICT	18/8	20
Library (New)	15/15	15

Table 2.1: The Allocations at some of the subnets in the UDSM LAN

The figures in Table 2.1 are always at the peak most of the times. To add on, the total bandwidth

allocated for the University is 155 Mbps (STM-1 allocation), and it overshoots (bursts) to 200 Mbps at times.

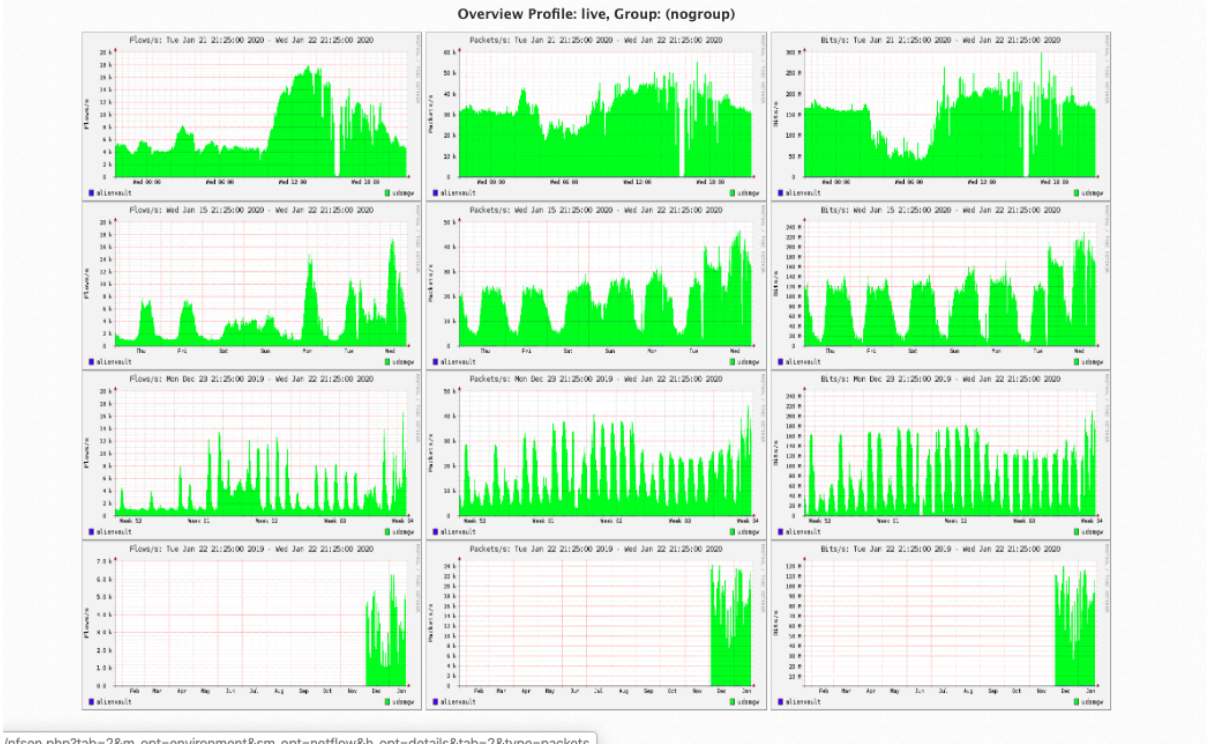

Figure 2.3: Traffic Profile in a range of 3 Days

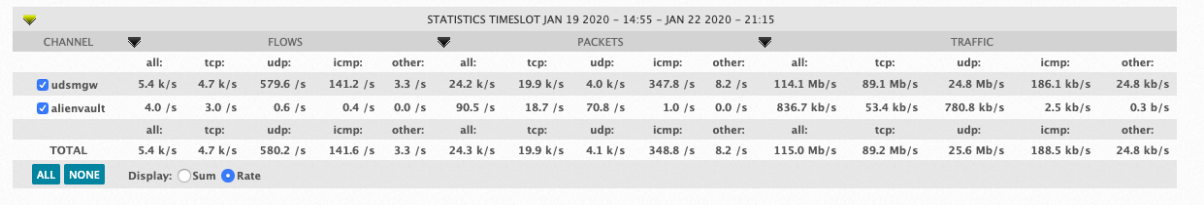

Figure 2.4: Traffic Rate in a range of 3 Days

Figure 2.5: Sum of traffic in a range of 3 Days

Figures 2.3, 2.4, and 2.5 depict the situation with which the UDSM traffic is in with respect to the protocols associated with the Internet. The figures show that the network is at the peak most of the times at daytime. Therefore, anyone modeling this network must make sure that it

depicts the current situation.

To make sure that the scenario depicted in the figures was correct, more work was done to capture how much data could be exchanged over the day time compared to that exchanged over the night time. A **ping** command was set at one of the computers—at CoICT—in the network for some days in Feb 2020, and the following data extract on Table 2.2 was obtained.

Date	**Destination Address**	**Time of the day**	**Packets sent**	**Packets received**	**Average Delay**	**%ge Loss**
Feb 3	196.44.161.196	Evening	4027	3453	2ms	14
Feb 3	8.8.8.8	Evening	3466	2663	113ms	23
Feb 4	8.8.8.8	Evening	1572	1269	464ms	19
Feb 4-5	8.8.8.8	Overnight	31701	29415	24ms	7
Feb 5	8.8.8.8	Daytime	9987	6267	UNDEFINED	37

Table 2.2: Ping statics to UDSM server (196.44.161.196) and Google (8.8.8.8) over the period of 3 days in February.

From the data extract above, it was observed that:

(i) The network is generally slow during daytime and it is characterized by higher numbers of packet losses.

(ii) The network has relatively low delays in the evening compared to daytime. This is,in one way, due to offices closing around the University, thus decrements in congestion.

(iii) The network is relatively fast at night and has less packet losses compared to both daytime and evening. This happens to be due to less number of user nodes in the network during night time.

(iv) There are times where the network is not reachable at all (*as depicted in Figure 2.6*). This situation dominates a lot at CoICT to the point that in order to obtain the data on general network performance and latency, I had to wait for the time when the network was available.

```
PING: transmit failed. General failure.
PING: transmit failed. General failure.
PING: transmit failed. General failure.
PING: transmit failed. General failure.
PING: transmit failed. General failure.
PING: transmit failed. General failure.
PING: transmit failed. General failure.
PING: transmit failed. General failure.
PING: transmit failed. General failure.
PING: transmit failed. General failure.
PING: transmit failed. General failure.
PING: transmit failed. General failure.
PING: transmit failed. General failure.
PING: transmit failed. General failure.
PING: transmit failed. General failure.
PING: transmit failed. General failure.
```

```
Reply from 41.86.177.33: Destination host unreachable.
Reply from 41.86.177.33: Destination host unreachable.
Reply from 41.86.177.33: Destination host unreachable.
Reply from 41.86.177.33: Destination host unreachable.
Reply from 41.86.177.33: Destination host unreachable.
Reply from 41.86.177.33: Destination host unreachable.
Reply from 41.86.177.33: Destination host unreachable.
Reply from 41.86.177.33: Destination host unreachable.
Request timed out.
Request timed out.
Request timed out.
Request timed out.
Request timed out.
Reply from 41.86.177.33: Destination host unreachable.
Reply from 41.86.177.33: Destination host unreachable.
Reply from 41.86.177.33: Destination host unreachable.
Reply from 41.86.177.33: Destination host unreachable.
Reply from 41.86.177.33: Destination host unreachable.
Reply from 41.86.177.33: Destination host unreachable.
```

*Figure 2.6: Some of the **ping** command responses on Feb 5, 2020 at one of the computers in the network*

To add on, the details on the preceding paragraphs were obtained from the current network topology at the University of Dar es Salaam in Figure 2.7.

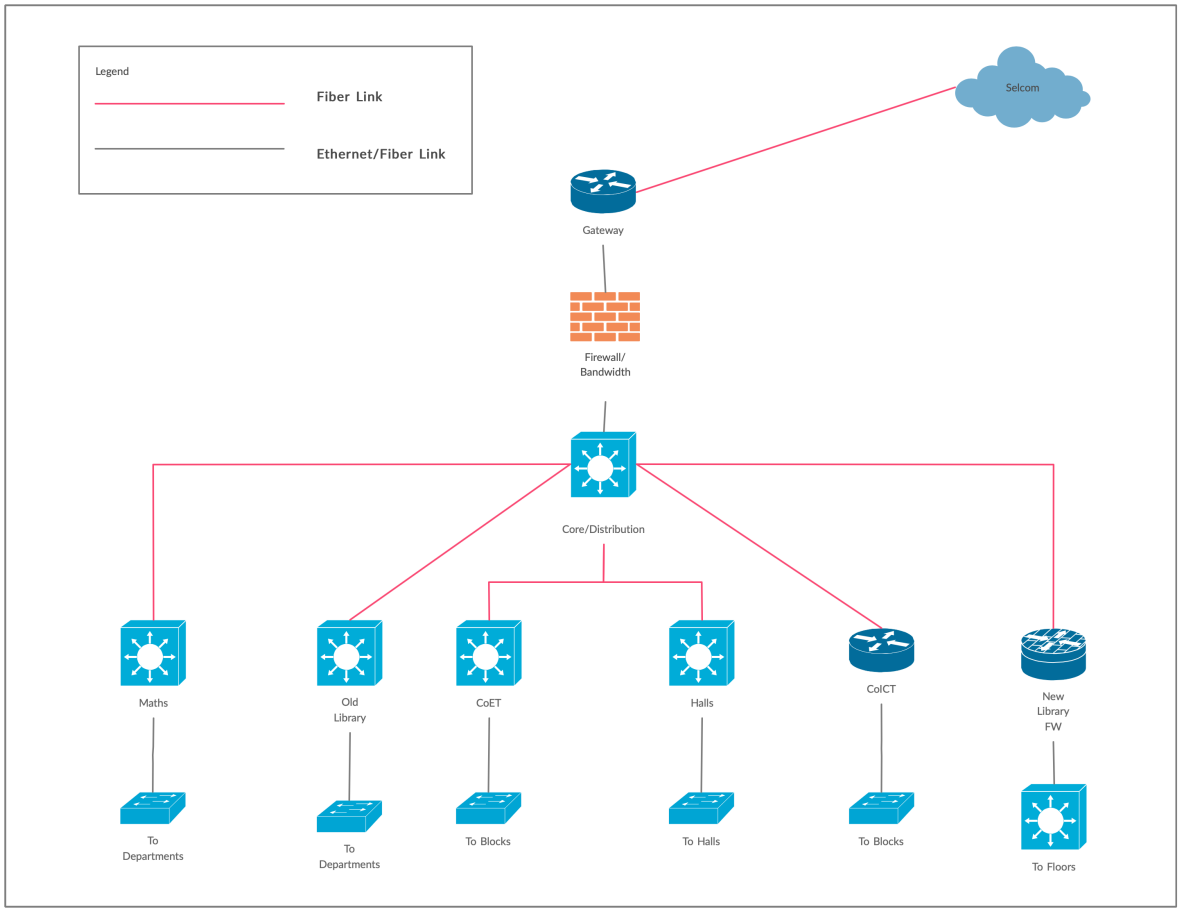

Figure 2.7: The current network topology at UDSM

2.3 Related Works and Systems

A range of studies suggested a possible hack on how to allocate the bandwidth depending on what IP addresses accessed what content and how often. One of the studies [12] sought to propose the dynamic bandwidth allocation model based on how the users rated the websites and how often the users would visit the websites. The work went further to develop the bandwidth allocation model and ended up comparing it to originally allocated bandwidth for the chosen websites, which proved to be an efficient approach. The idea in this work means that it could be extended to dealing directly with the IP addresses, which is correct, and that the bandwidth allocation could be done depending on who access what and from what context.

However, there are a number of companies that use bandwidth scaling, which is the feature that allows the network operators to increase or decrease the bandwidth allocations based on how much traffic there is in the network [13]. The technique relies on the insights of the network operators, hence no intelligence in traffic is associated with the bandwidth allocations.

To address the problems associated with bandwidth management and allocation, different network monitoring systems were developed. These are explained in the following paragraphs.

Nagios is one of the leading in industry providing monitoring solutions for small and enterprise level of infrastructure. It monitors different components including network protocols, operating systems, system metrics, applications, services, web servers and middle ware systems. It also provides detailed status information on all devices, alerts on configured features of the system via e-mail, SMS, or custom scripts, and generally helps the users plan for future upgrades and even integrate with in-house or third-party applications due to multiple APIs.
Nevertheless, one has to be very specific when telling the system what to monitor.

Cacti is another open source network monitoring tool which can be installed on Linux and Windows operating systems. It can be connected to round robin database tool (RRDT) which allows to generate graphs related to relevant network data. It requires MySQL database in order to work fine.

Zabbix is another network monitoring tool. Like Nagios, Zabbix was designed to monitor everything from performance and availability of servers, network equipment to web applications and databases. Its server-agent system architecture where an agent is installed on a server (a client being monitored). It has an advantage that it can be installed on Linux, Windows, Solaris, MacOS, FreeBSD, OpenBSD and supports SNMP for better reporting.

Icinga started as a fork of Nagios in 2009. Icinga monitors network and host services, severs and components, provides support for event handlers and notifications, and has a choice between Classic UI and Icinga web in operational user interfaces.

OpenNMS is another tool that allows to collect systems information using SNMP, HTTP, and others. With OpenNMS one can discover layer two network topologies in their network. It is built on event-driven architecture. Its full package comes in with device temperature monitoring, IPv4 and IPv6 support and geographical node map to show nodes and service outages using Open Street Map, Google Maps or MapQuest. It has limited resources for development and maintenance.

Although a thorough review was done and the mentioned tools were tested, none of them provides the ability to manage the bandwidth. The best that they can do is to provide graphs for visualization of bandwidth utilization in the network. None of them does analysis of the utilization of the bandwidth and therefore requires human intervention in trying to manage the bandwidth.

The focus of this work, therefore, was to devise the method which employs the machine learning model that determines where and when to allocate the resources without involving the network operators in the process.

Chapter 3

Methodology

3.1 Introduction

The methodology in this study consisted of three activities as summarized in Figure 3.1 and explained in the next sections.

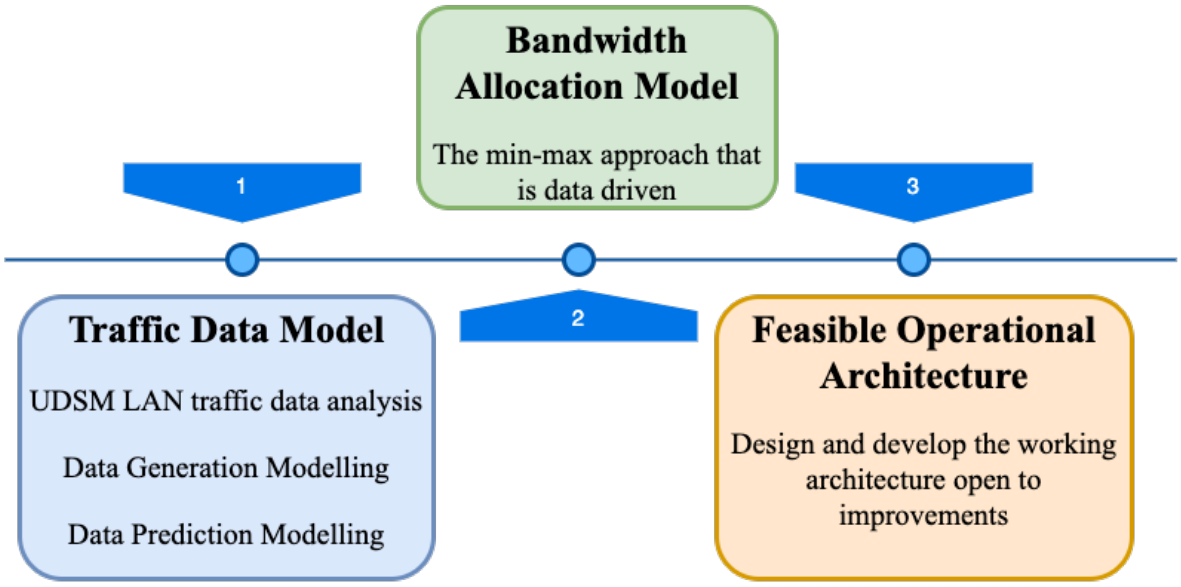

Figure 3.1: The Methodology

3.2 Development of a Traffic Learning and Prediction Model

To attain bandwidth allocation in the subnetworks, the insights from the data obtained—in chapter 2—had to be extracted. These insights were then used to develop network traffic generation and prediction models. The data generation model was implemented in python, taking into account the stochastic nature of the IP traffic data.

The traffic learning and prediction model was designed, developed and implemented in python. The model took advantage of the available python **statsmodels** and **patsy** libraries. These libraries helped to model the poisson regressor without having to write one from scratch. The learning was done in three different phases. Each of these phases was done independently while the simulation time was differentiated from each of them. At first, it was determined how much

the current traffic would depend on the past two data points—which performed worse in the prediction, while in the next two the predictions were made with respect to three and nine past traffic data points respectively.

Despite their better performances in other kinds of data, Time Series Forecasting Models (TSF) and Neural Networks (NN) were not used. This was due to the fact that the data produced for study would do better with a poisson regressor due to its nature.

3.3 Development of the Bandwidth Allocation Model

The analyses done from the development of a traffic learning and prediction model made it easy to understand the nature of the traffic and the underlying predictions. This was followed with the mathematical analysis which produced a simple equation that would later be used to divide the bandwidth amongst the network elements in the network core depending on the amount of traffic that comes in and goes out of such elements. The developed equation considered the mean of the predictions as observed in the outputs from running simulations. The implementation in this phase was done in python.

3.4 Development of the Operational Architecture

The feasible operational architecture was developed after a thorough review of SDN and associated technologies. The operations involving bandwidth allocation, traffic analysis and prediction in the core network were centralized. This was due to the fact that the bandwidth allocated for an institution is configured along the transmission line between its point of presence (POP) and the Internet service provider (ISP) premises. Therefore, it would be the central router or the core network that managed the bandwidth resources allocated for the institution.

Chapter 4

Data Analysis and Algorithm Development

In this chapter, an implementation of UDSM LAN—Figure 2.7—in NS3 (A Network Simulation platform) is explained. It is followed by the development of traffic generation model. These two were needed in the study and further analysis of the LAN so that traffic prediction model could be developed.

4.1 UDSM Network Topology Implementation in NS3

The following comment extracts from the code— Figure 4.1 and Figure 4.2—show the considerations made in writing the code for the configuration of the network.

```
/*
 * ============================================================================
 *       Author: Emmanuel Julius Samson
 *        Reg #: 2016-04-01802
 *       Degree: B.Sc. Telecommmunications Engineering (2020)
 *    FYP Title: IP Networks QoS Optimization using ML and SDN
 * ============================================================================
 *
 *
 *                          A simplified extract of the UDSM LAN
 *                 NB: The FW/BW node has not been implemented in the code
 *  ______________________________________________________________________________
 * |                                                                              |
 * |                               Gateway Router to Selcom                       |
 * |                                        |                                     |
 * |                                        |                                     |
 * |                                      FW/BW                                   |
 * |                                        |                                     |
 * |                                        |                                     |
 * |                               Core Distribution switch                       |
 * |                                        |                                     |
 * |                                        |                                     |
 * |   ===================================================================        |
 * |   |               |            |            |            |             |     |
 * |   |               |            |            |            |             |     |
 * | Maths_Switch    Old_Library     CoET        Halls        CoICT_Router   New_Lib_Router  |
 * |   |               |            |            |            |             |     |
 * |   |               |            |            |            |             |     |
 * | Switch           Switch       Switch       Switch       Switch        Switch  |
 * | To_Depts        To_Depts     To_Blocks     To_Halls     To_Blocks     To_Floors |
 * |                                                                              |
 * |______________________________________________________________________________|
 *
 *
 * ============================================================================
 *
 * Tasks:
 *   1. Create the network nodes
 *   2. Install the internet stack on each of the nodes
 *   3. Attach one or more network devices on each node and attach the device to channel
 *   4. Create the network interface for each network device
 *   5. Assign an IP address to each network interface
 *
 * ============================================================================
```

Figure 4.1: UDSM Network Topology Implementation extract in NS3

```
47      ================================================================================================
48
49      Necessary Configurations:
50      ------------------------------------------------------------------------------------------
51      Routers:
52        1. Gateway        : routers[0]    -- subnet1
53        2. CoICT_Router   : routers[1]    -- subnet6
54        3. New_Lib_Router : routers[2]    -- subnet7
55
56      Distribution Switches:
57        1. Core Distribution Swich : distribution_switches[0]   -- subnet1 || subnet 2 - 7
58        2. Maths                   : distribution_switches[1]   -- subnet2
59        3. Old Library             : distribution_switches[2]   -- subnet3
60        4. CoET                    : distribution_switches[3]   -- subnet4
61        5. Halls                   : distribution_switches[4]   -- subnet5
62
63      Access switches:
64        1. Maths/To_Departments         : access_switches[0]    -- subnet20
65        2. Old_Library/To_Departments   : access_switches[1]    -- subnet30
66        3. CoET/To_Blocks               : access_switches[2]    -- subnet40
67        4. Halls/To_Halls               : access_switches[3]    -- subnet50
68        5. CoICT_Router/To_Blocks       : access_switches[4]    -- subnet60
69        6. New_Lib_Router/To_Floors     : access_switches[5]    -- subnet70
70
71      ------------------------------------------------------------------------------------------
72
73
74      ================================================================================================
75
76  */
77
```

Figure 4.2: UDSM Network Topology Implementation Configuration extract in NS3

To begin with, the point-to-point connection between the Gateway and the core distribution switch was put into a single subnet (*subnet1*). This allows for the assignment of IP addresses to their specific interfaces which allows for communication between them. This configuration has been carried out throughout the network; bringing together the network nodes—switches and routers—that were needed to be together in single or multiple subnets. However, any subnet—that came at the access level—was named, hence configured by the preceding subnet at the distribution nodes with a leading zero (0).

4.2 IP Traffic Data Generation

The amount of data exchanged between serves and clients in server-client configurations in IP networks is purely stochastic and follows the count based scenario—the on-off traffic generation sources that come and go during network operations. That means, the timing of the generation of traffic data is purely random but the average of traffic generated/exchanged (μ) per unit time is known. This is the characteristic of the Poisson distribution as depicted in

equation 4.1. It is this feature, this work considers, that suggests closely related traffic shapes during the day and night times.

$$P(X = x) = \frac{\mu^x}{x!} exp(-\mu) \tag{4.1}$$

In equation 4.1, μ is the average of the amount of data traffic generated per unit time and x is the amount of data traffic generated in a given time. $P(X = x)$ is the probability that variable X is equal to value x at a given interval of time.

Considering the data in Figure 2.4, the following information was found useful to consider in the generation of traffic data points.

	TCP	UDP	ALL
Flows	4700/s	579.6/s	5400/s
Packets	19900/s	4000k/s	24200/s
Traffic	89.1Mb/s	24.8Mb/s	114.1Mb/s

Table 4.1: Traffic Data Excerpt from Figure 2.4

Having determined the amount of data flowing through the network per second, i.e. $114.1Mbps$, the traffic was then distributed among the major network access nodes with respect to the allocations in Table 2.1. It is also from this table that it was observed that the amount of bandwidth allocated for each sub-network in traffic burst times was $124Mbps$, the value that is a little higher than the average traffic in three days as shown in Table 4.1. The traffic occupied at least 92% of the bandwidth allocated for each for burst times. This further suggests that the allocated bandwidth for each sub-network did not consider the fact that the traffic would, in most times, be higher than the allocated bandwidth.

Therefore, with above considerations in mind, the traffic generation algorithm considered that the average traffic data in each sub-network was 0.92 times the amount allocated for burst periods, as shown on Table 4.2.

Subnet	Burst (Mbps)	Average Traffic (Mbps) $0.92 \times Burst$
Maths	35	32.2
Lib	10	9.2
CoET	25	23
Hall5	16	14.72
CoICT	20	18.4
Library (New)	15	13.8

Table 4.2: The Allocations at some of the subnets in the UDSM LAN

Since the average delay data from Table 2.2 was not sufficient to calculate the average delays over the period of time, $350ms$ was assumed the delay of the network during busy times (daytime). Hence, the following data generation program logic was implemented in python (see Appendix B) to generate the traffic data.

```
Record program starting_time
Initialize transmission_time[]
Initialize start_transmission_time[]
Initialize packets_transmitted[]

while(current_time - starting_time) < simulation_time:
    Append current_time to start_transmission_time[]
    Append randomly generated packet_number to packets[]
    Randomly select transmission_time (average = 350ms)
    Append transmission_time to transmission_time[]

Pack start_transmission_time[], transmission_time[] and
   packets_transmitted together

Write the data to file for storage and further processing
```

Thereafter, the program was run for five minutes and the following extract of data points—Figure 4.3—was obtained.

913 lines (913 sloc) | 36.8 KB Raw Blame

Search this file...

	Start_Time	Transmission_Duration	Packets
2	2020-07-24 17:38:10.658045	0.359	19467
3	2020-07-24 17:38:11.017493	0.316	23150
4	2020-07-24 17:38:11.337716	0.292	24783
5	2020-07-24 17:38:11.630864	0.34600000000000003	20392
6	2020-07-24 17:38:11.977492	0.38	19399
7	2020-07-24 17:38:12.360392	0.36	24277
8	2020-07-24 17:38:12.725418	0.334	20766
9	2020-07-24 17:38:13.063216	0.34400000000000003	20713
10	2020-07-24 17:38:13.410676	0.318	24539
11	2020-07-24 17:38:13.729963	0.376	19597
12	2020-07-24 17:38:14.106243	0.34800000000000003	20403
13	2020-07-24 17:38:14.459585	0.385	22417

Figure 4.3: Data Generated by the traffic generation algorithm

It is, however, most important to note that the data generation algorithm above considered the main features for the prediction of traffic as highlighted in the article [14]. It is stated that there are two major traffic parameters generated by network traffic models:

(i) Packet length distribution and

(ii) Inter-arrival distributions

Other parameters such as routes, distribution of destinations, e.t.c. are of less importance.

To prove the stochastic distribution of the generated packets data, the code below was written for reading the data.

```
import pandas as pd
import matplotlib.pyplot as plt

data = pd.read_csv('data_points.csv')

plt.hist(data["Packets"], bins=100)
plt.xlabel("Number of Packets")
```

```
    plt.ylabel("Relative number of Generations")
    plt.title("The Distribution of Generated Packets")
    plt.savefig("hist_dist.png")
    plt.show()
```

The output of the code was Figure 4.4, which clearly shows how random the data generation was.

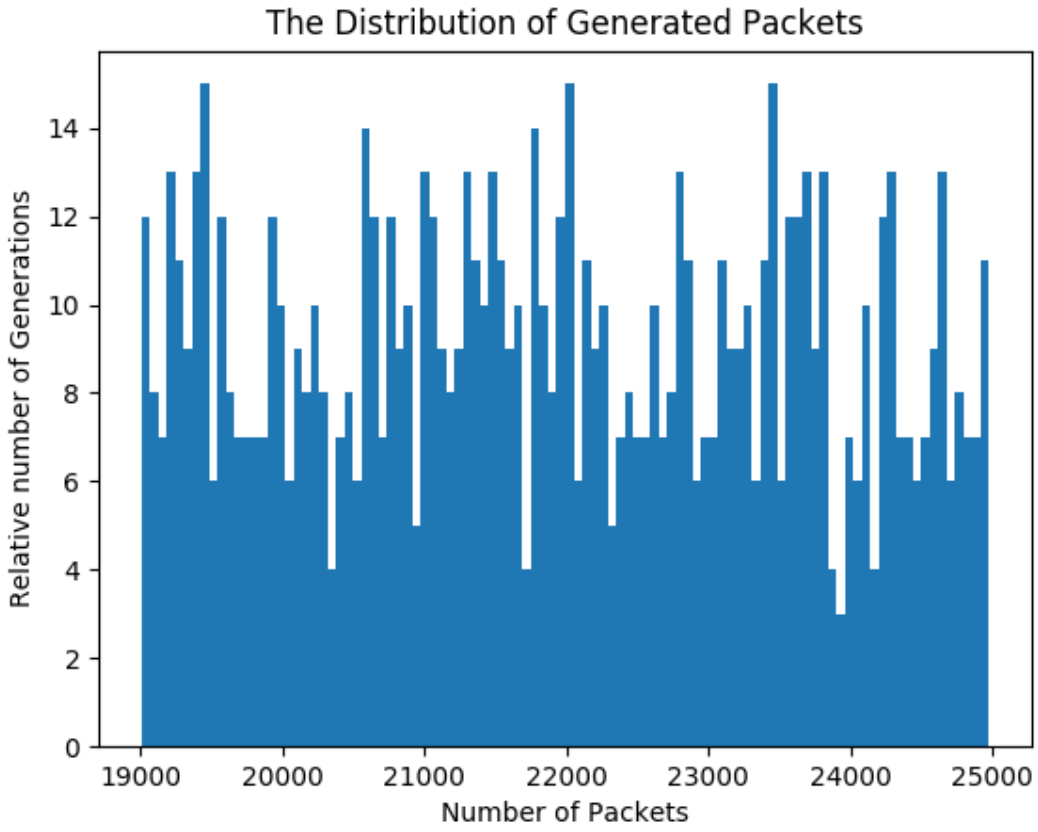

Figure 4.4: Generated Packets Distribution

The distribution of the inter-arrival times was also investigated. The following piece of code was used to determine the distribution of the inter-arrival times, and Figure 4.5 was produced. Therefore, with Figures 4.4 and 4.5, it was to the satisfaction that the data produced correlated with the stochastic nature of the IP networks data generators. Hence, further considerations for the ML algorithm for traffic learning and prediction followed.

```
    import pandas as pd
    import matplotlib.pyplot as plt
```

```
3
4     data = pd.read_csv('data_points.csv')
5
6     plt.hist(data["Transmission_Duration"], bins=100)
7     plt.xlabel("Inter-arrival times in seconds")
8     plt.ylabel("Relative number of Generations")
9     plt.title("The Distribution of Inter-arrival times")
10    plt.savefig("trans_dist.png")
11    plt.show()
```

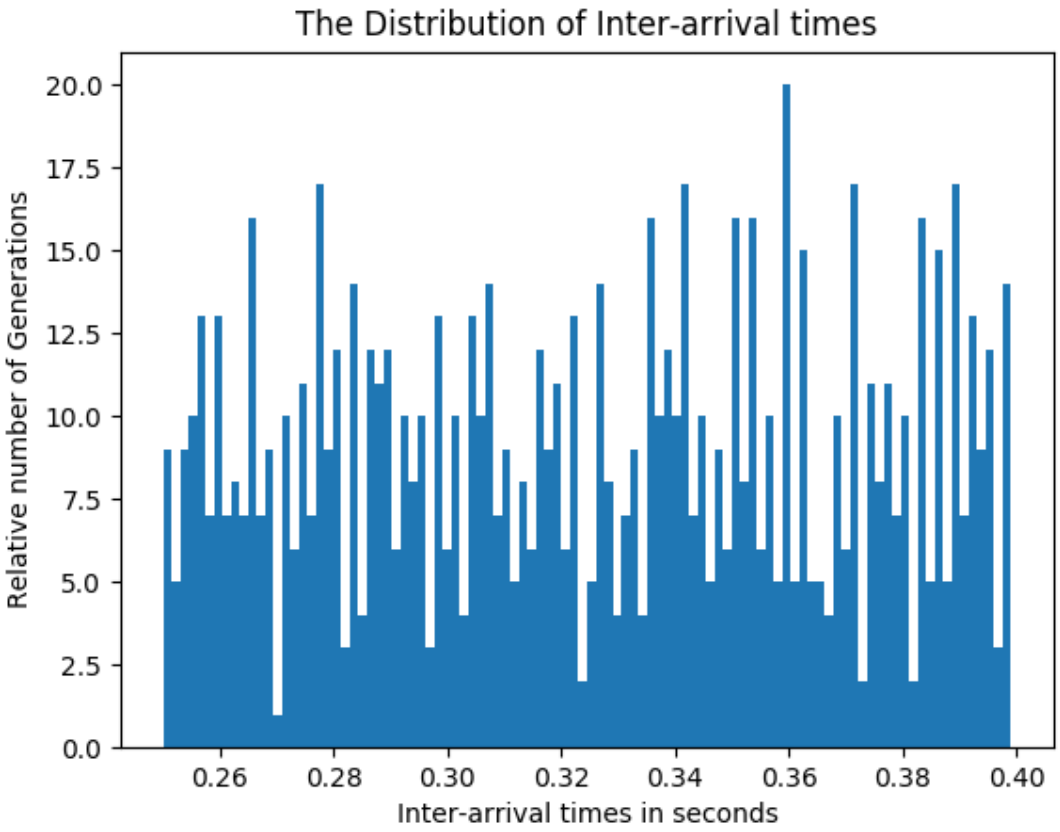

Figure 4.5: Generated Inter-arrival times Distribution

4.3 IP Traffic Data Prediction With Poisson Regression

Considering the context of the IP networks, and the nature of the data that gets produced over time, it was necessary to consider the fact that the sequence with which the data gets produced is important in modeling the data traffic prediction algorithm. It is with this in mind that the

data produced in the previous section was further modified to produce data extract in Figure 4.6. In this, *packets_4* was made the dependent variable while *packets_1, packets_2*, and *packets_3* were made the independent variables; making it a necessity that the next amount of traffic would depend on the past three observed values.

910 lines (910 sloc) | 22.2 KB Raw Blame

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	packets_1	packets_2	packets_3	packets_4
2	19467	23150	24783	20392
3	23150	24783	20392	19399
4	24783	20392	19399	24277
5	20392	19399	24277	20766
6	19399	24277	20766	20713
7	24277	20766	20713	24539
8	20766	20713	24539	19597
9	20713	24539	19597	20403
10	24539	19597	20403	22417
11	19597	20403	22417	22690
12	20403	22417	22690	22512

Figure 4.6: Data extracts after dividing them into sequences

Hence, the prediction used the **patsy** and **statsmodels** libraries in python to develop the training and prediction model (see Appendix C). The code produced the results in Figures 4.7 and 4.8. This—despite meeting the prediction goal—didn't prove to be a fine model for prediction of individual traffic. That is because due to the stochastic nature of the data, the model didn't fit perfect and ended up predicting the average traffic most of the time.

Nevertheless, the prediction correlated with the poisson model with unchanging mean. In networks that need individual packet flow level monitoring, however, it would perform worse; it would recommend almost the same amount of bandwidth every time—despite some gradual variations—which would be unnecessary because the static allocation would do better on that.

The analysis of networks, however, considers the contingencies associated with the networks. This guess work (supported by analysis and client needs) that could, in one way or the other, determine the mean traffic that would be produced by a subnetwork during its operation should

suggest the amount of bandwidth necessary to be allocated. It is, therefore, this knowledge that would later be implemented in **typical data driven network operations** to determine the trends thereby predicting the **mean** of the traffic that would necessarily be allocated bandwidth for depending on what has been happening in the past (in minutes, hours, e.t.c). Consequently, the mean of the traffic would keep changing from time to time depending on the number of access nodes at the network access layer (Figure 5.3) and the amount of traffic that one initiates.

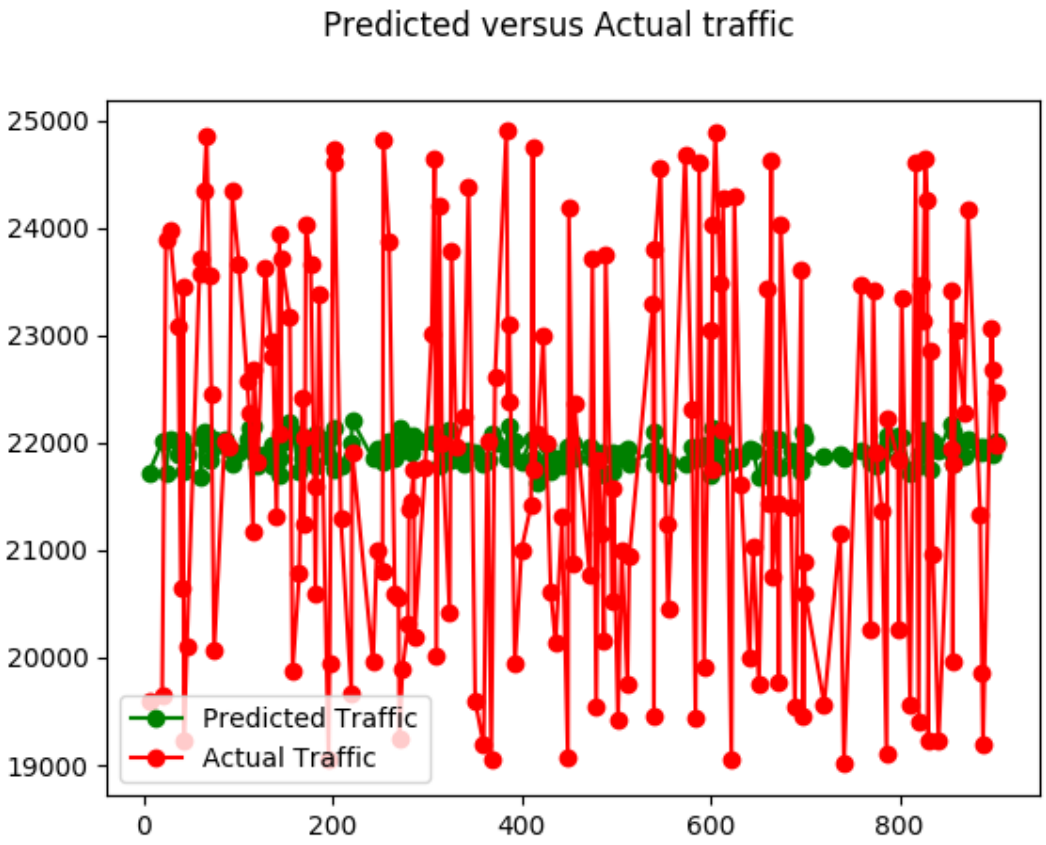
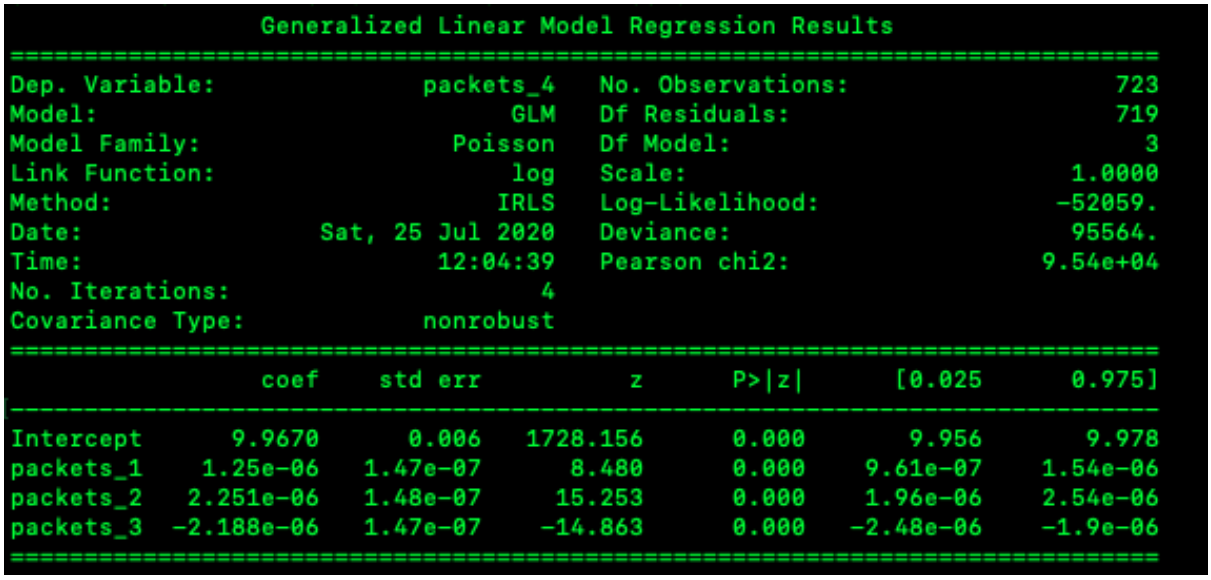


Figure 4.7: Predicted Traffic against Actual Traffic with respect to the past THREE data points



Generalized Linear Model Regression Results

Dep. Variable:	packets_4	No. Observations:	723
Model:	GLM	Df Residuals:	719
Model Family:	Poisson	Df Model:	3
Link Function:	log	Scale:	1.0000
Method:	IRLS	Log-Likelihood:	-52059.
Date:	Sat, 25 Jul 2020	Deviance:	95564.
Time:	12:04:39	Pearson chi2:	9.54e+04
No. Iterations:	4		
Covariance Type:	nonrobust		

	coef	std err	z	P>|z|	[0.025	0.975]
Intercept	9.9670	0.006	1728.156	0.000	9.956	9.978
packets_1	1.25e-06	1.47e-07	8.480	0.000	9.61e-07	1.54e-06
packets_2	2.251e-06	1.48e-07	15.253	0.000	1.96e-06	2.54e-06
packets_3	-2.188e-06	1.47e-07	-14.863	0.000	-2.48e-06	-1.9e-06

Figure 4.8: Generalized model results for 3 past data points

From Figure 4.8, it can be noted that the mathematical model could be summarized by the general poisson regression equation 4.2:

$$\lambda_n = \exp\left(\beta_0 + \beta_1\lambda_{(n-1)} + \beta_2\lambda_{(n-2)} + \beta_3\lambda_{(n-3)}\right) \tag{4.2}$$

Where:

- λ_n Traffic generated at point *n*
- β_0 The bias of a regressor = 9.9670
- β_1 The coefficient for traffic at *n-1* = 1.256e-6
- β_2 The coefficient for traffic at *n-2* = 2.251e-6
- β_3 The coefficient for traffic at *n-3* = -2.188e-6

Therefore equation 4.2 becomes:

$$\lambda_n = \exp\left(9.9670 + 1.25e{-}6\lambda_{(n-1)} + 2.25e{-}6\lambda_{(n-2)} - 2.188e{-}6\lambda_{(n-3)}\right) \tag{4.3}$$

The coefficients in equation 4.3, however, will change from time to time depending on the available data for processing. This was determined when the simulation was run for 15 minutes, producing 2743 data points. Then, the prediction algorithm was run on the data taking the past 9 traffic points as the determinants of the 10^{th}. Figure 4.9 was the output of such training and prediction while Figure 4.10 was the output of the trained model.

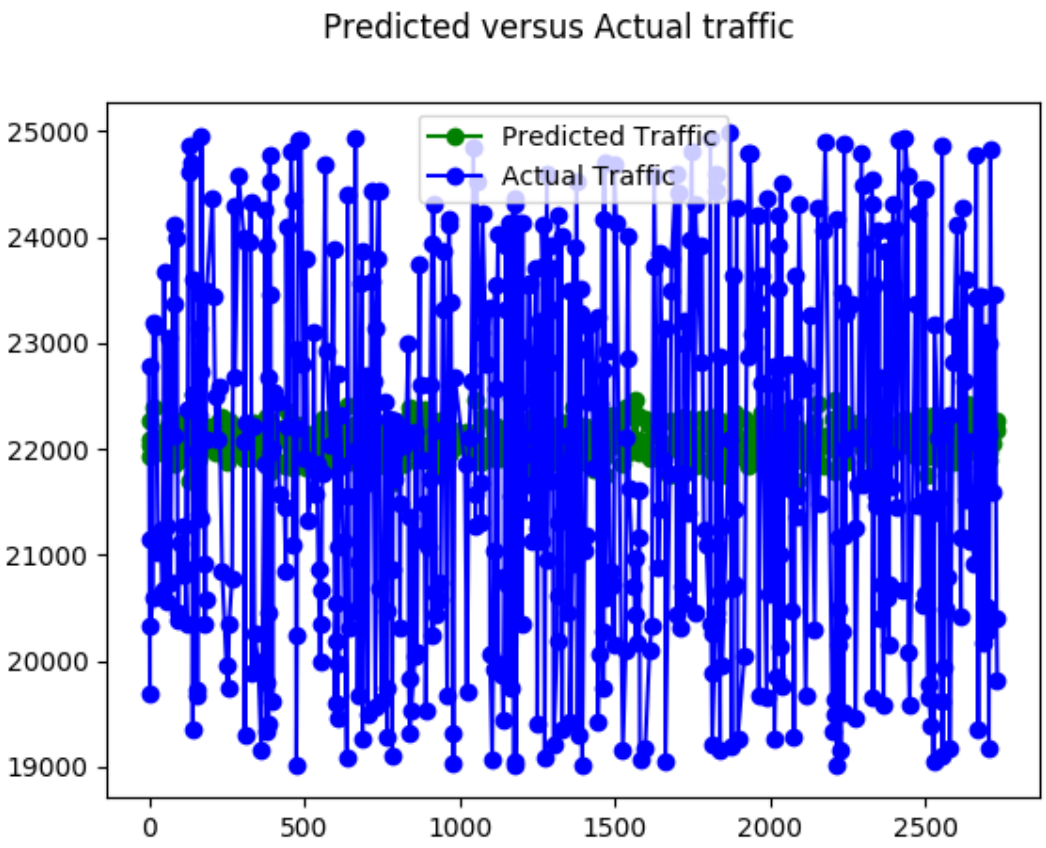


Figure 4.9: Predicted Traffic against Actual Traffic with respect to the past NINE data points

Generalized Linear Model Regression Results

Dep. Variable:	packets_10	No. Observations:	2176
Model:	GLM	Df Residuals:	2166
Model Family:	Poisson	Df Model:	9
Link Function:	log	Scale:	1.0000
Method:	IRLS	Log-Likelihood:	-1.5945e+05
Date:	Thu, 30 Jul 2020	Deviance:	2.9314e+05
Time:	15:24:20	Pearson chi2:	2.93e+05
No. Iterations:	4		
Covariance Type:	nonrobust		

	coef	std err	z	P>|z|	[0.025	0.975]
Intercept	10.0693	0.006	1761.470	0.000	10.058	10.081
packets_1	-1.463e-06	8.39e-08	-17.436	0.000	-1.63e-06	-1.3e-06
packets_2	-1.504e-06	8.4e-08	-17.911	0.000	-1.67e-06	-1.34e-06
packets_3	2.335e-06	8.38e-08	27.852	0.000	2.17e-06	2.5e-06
packets_4	-1.131e-07	8.41e-08	-1.345	0.179	-2.78e-07	5.17e-08
packets_5	6.282e-07	8.42e-08	7.460	0.000	4.63e-07	7.93e-07
packets_6	-4.585e-07	8.44e-08	-5.430	0.000	-6.24e-07	-2.93e-07
packets_7	-2.055e-06	8.42e-08	-24.404	0.000	-2.22e-06	-1.89e-06
packets_8	-5.466e-07	8.48e-08	-6.447	0.000	-7.13e-07	-3.8e-07
packets_9	1.272e-07	8.38e-08	1.517	0.129	-3.71e-08	2.92e-07

Figure 4.10: General model results for 9 past data points

Hence, the linear model in equation 4.2 could be simply summarized to produce a modified equation 4.4 as follows:

$$\lambda_n = \exp\left(\beta_0 + \sum_{m=1}^{n-1} \beta_m \lambda_{n-m}\right) \tag{4.4}$$

The symbols have the same meaning as in equation 4.2

4.4 Bandwidth Optimization Algorithm

From the findings in the two preceding sections, it was found out that bandwidth optimization could easily be determined by considering **the mean of the predicted traffic data** from each subnetwork utilizing the total allocated bandwidth. Hence, equation 4.5 was devised; setting a foundation for bandwidth allocation algorithm that allocates resources depending on the usage of one subnetwork against the others.

$$\gamma_i = \frac{\mu_{\lambda_i}}{\sum_{i=1}^{n} \mu_{\lambda_i}} \times \Gamma \tag{4.5}$$

Where:

γ_i Bandwidth allocated to subnetwork *i*

μ_{λ_i} Predicted mean of the traffic at subnetwork *i*

Γ Total allocated traffic at the core network

And,

$$\mu_{\lambda_i} = \frac{\sum \lambda_i}{n} \tag{4.6}$$

n is the number of traffic points in the test set.

With those equations in the mind, and the observations from the preceding sections, the flowchart in Figure 4.11 was devised to depict the typical process that would achieve traffic prediction and bandwidth allocation during the network operations.

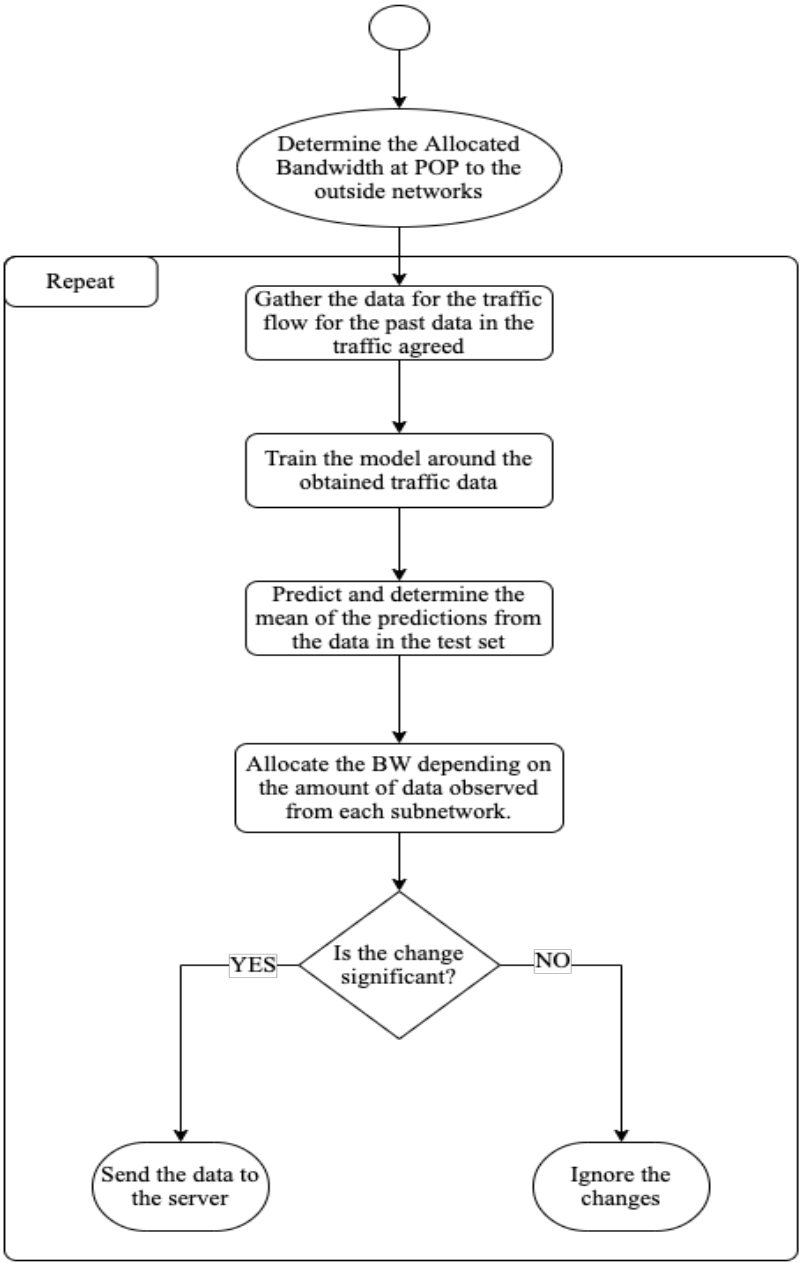


Figure 4.11: Bandwidth Allocation Algorithm Flowchart

The algorithm in Figure 4.11 considers the packets sent in every established flow.

Chapter 5

Proposed Operational and Architecture Designs

In chapter 4, this work went into details on the analysis and considerations done in the development of the bandwidth allocation algorithm. Also, as addressed in chapter 1, this work aimed at proposing the operational model and architecture designs which would support the implementation of the solution. Therefore, these designs and considerations are explained. The designs can be customized to suit specific network requirements.

5.1 Operational Model Design

For production purposes, the proposed Internet traffic data driven bandwidth allocation algorithm is expected to be shipped with other supporting scripts. In so doing, the whole system should run in two different places; on the server and on the router. Internet traffic data processing, learning and prediction, and bandwidth allocation scripts would be run on the server while actual bandwidth allocation would be run on the router.

The server should be responsible for hosting the running scripts and therefore responsible for providing the necessary operational environment including the python interpreter.

The router will also be responsible for providing configuration success notification which will help to tell whether it is needed to repeat the configurations in case they proved failure.

There should be one or more python (or any other language) scripts together with the bandwidth allocation algorithm which, in their collection, will be responsible for the following:

(i) Calculate and allocate initial minimum bandwidth for each router interface

(ii) Connect the server to the router via telnet (or any other access method thought necessary)

(iii) Capture the Internet traffic data from each interface on the router

(iv) Predict the Internet traffic for each interface in the interval of time agreed depending on how critical the network is deemed to be.

(v) Call for bandwidth allocation algorithm, and provide it with the predicted traffic values

(vi) Allocate bandwidth for each interface depending on the provided predicted traffic values

(vii) Prepare the configuration scripts and send them to the router

(viii) Configure the router depending on the prepared configuration scripts

(ix) Determine whether the configurations done were successful

(x) Prepare and store configuration logs for future reference

Therefore, Figure 5.1 depicts the typical sequence diagram of the operations between the server and the router while Figure 5.2 summarizes the operational model design for the two major entities for the correct operation of the algorithm.

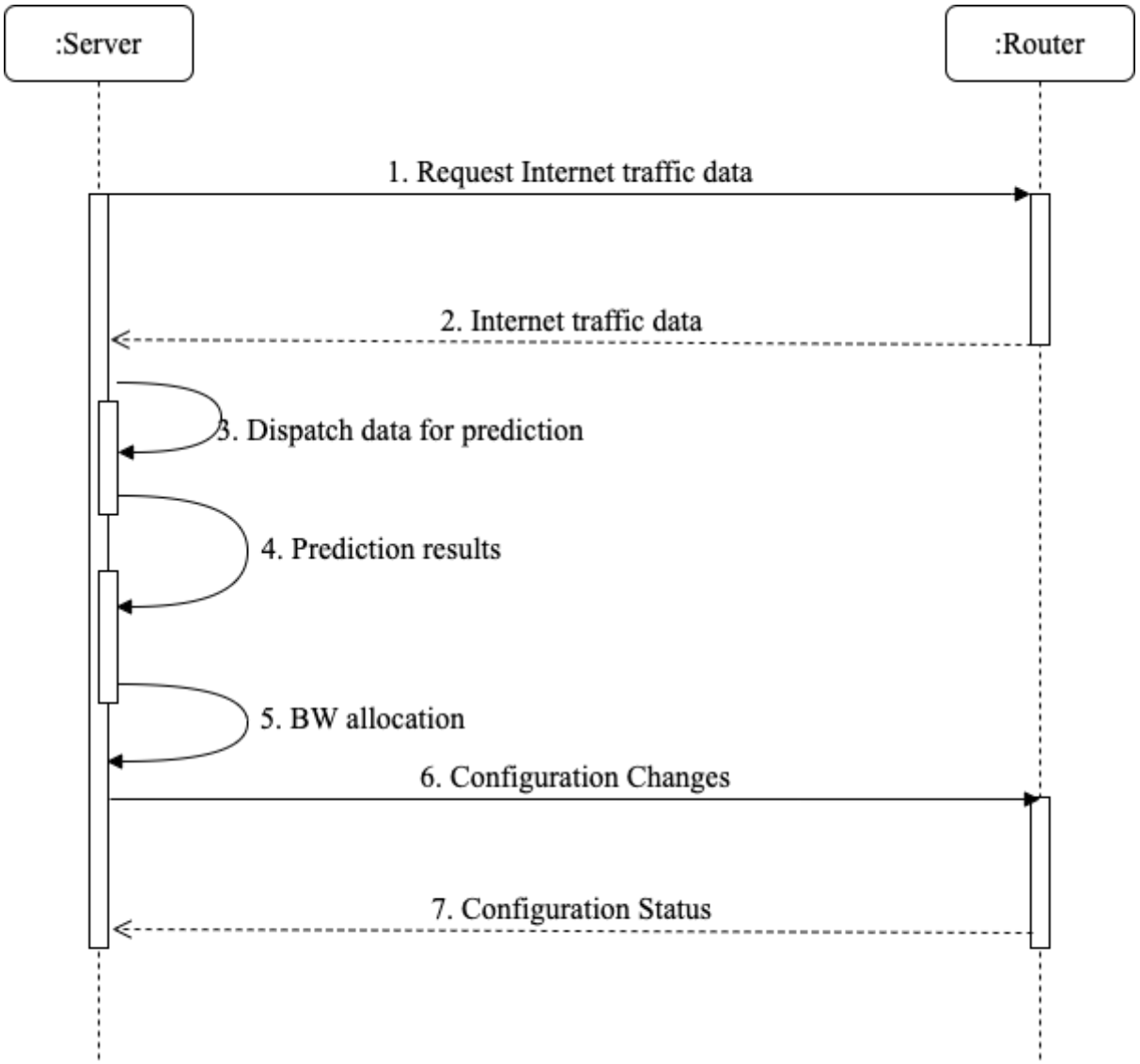


Figure 5.1: The Sequence Diagram for the operations

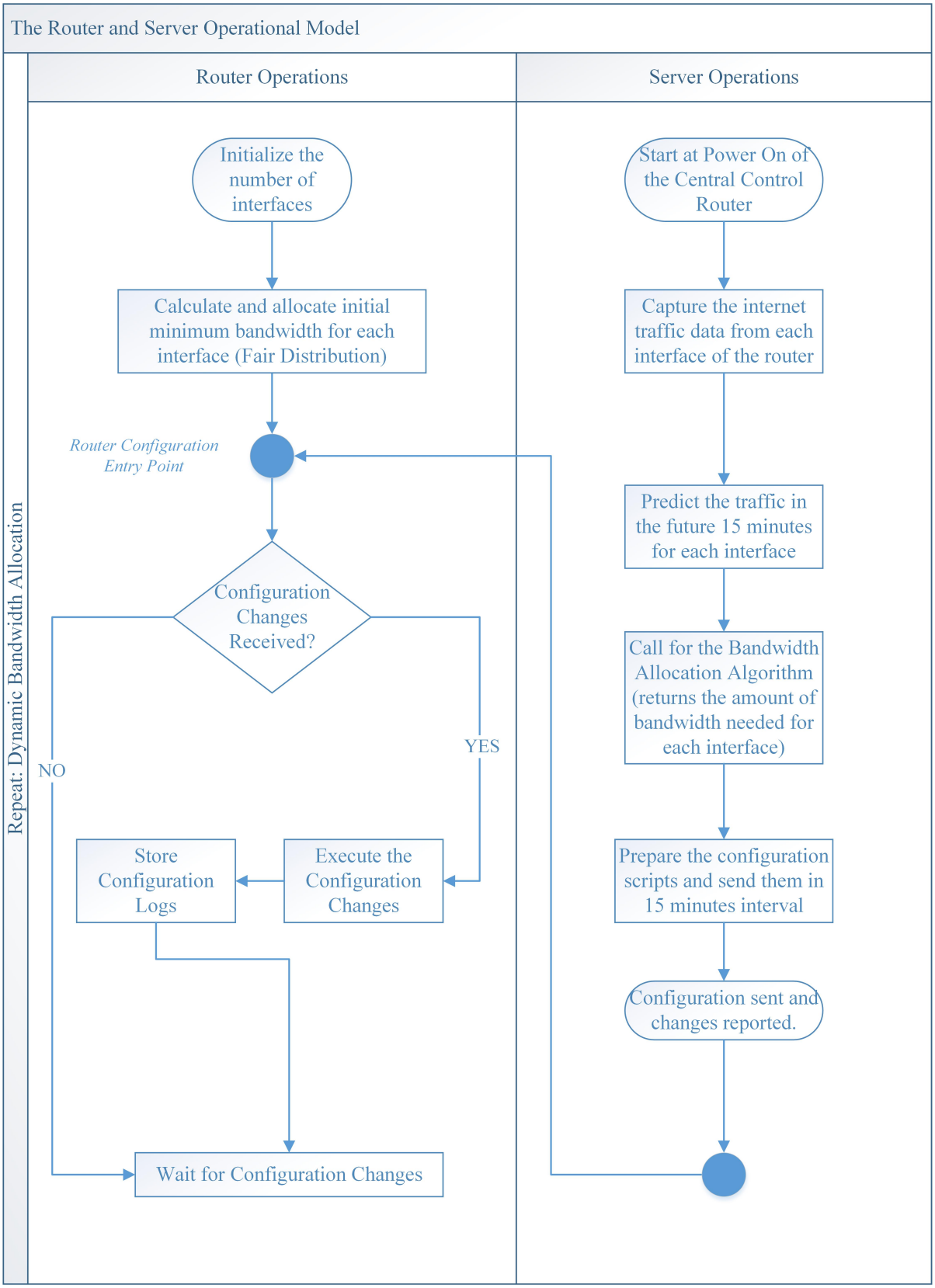


Figure 5.2: The Router and Server Operational Model

5.2 Architecture Design

The architecture of the system, Figure 5.3, consists of four major layers. The Internet traffic data generation layer is where all the devices sharing the data over the Internet are found. After the devices generate the data, packet initiation and delivery layer that consists of switches that are responsible for packet delivery comes in, then the routing services access layer follows which is responsible for routing the data over the IP layer. The fourth layer is where this work was focused at. It is where the network operations, traffic data analysis and bandwidth allocation are to be done.

With this configuration, the application of SDN would be realized in case there is more than a single router at the core of the network. This architecture ensures that the network core operations are focused on the data that is generated at the interfaces at the core (Layer 4).

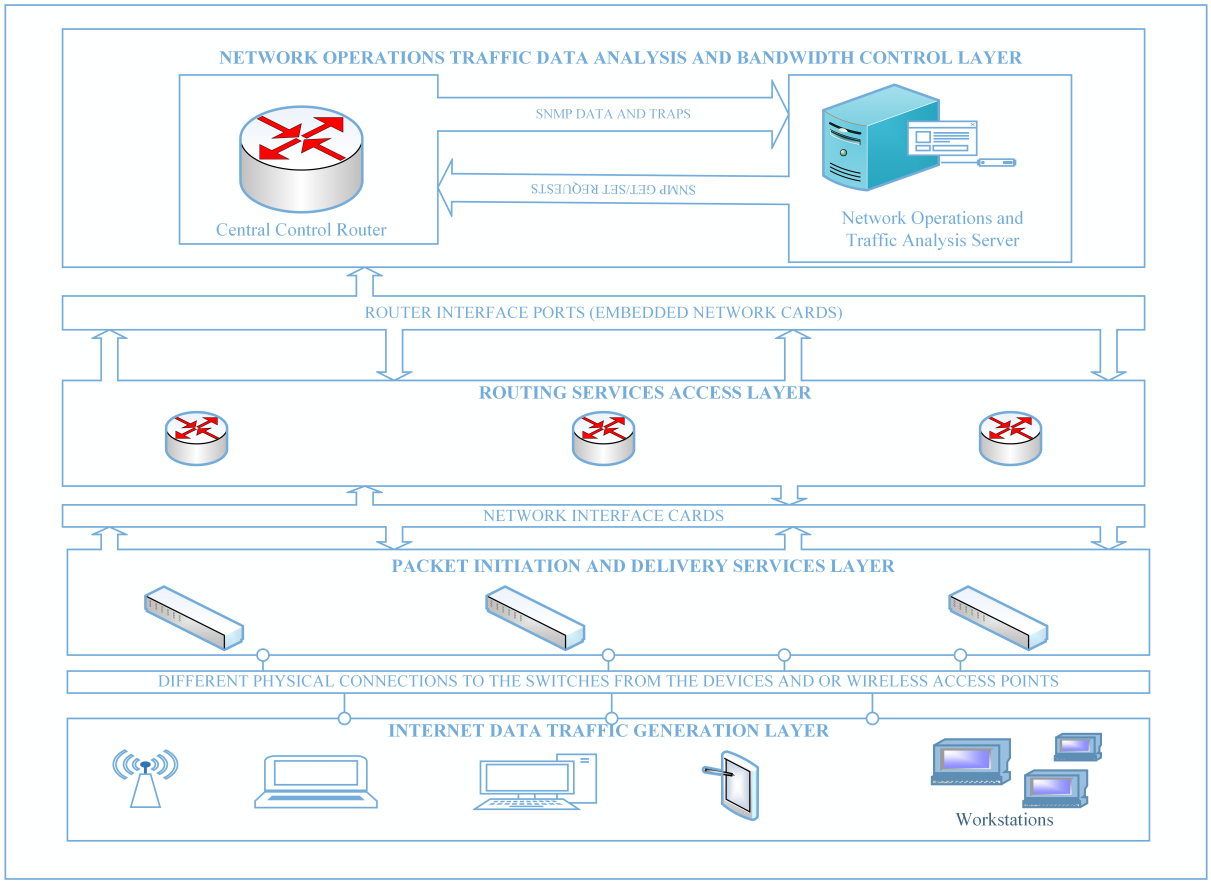


Figure 5.3: The Architectural Design of the Operational Environment

Chapter 6

Conclusion

In conclusion, the contributions of this work are summarized and some important observations are noted. Some areas that can extend this work beyond the stated limitations are also suggested.

6.1 Contributions

The contributions of this work are summarized as follows:

1. **The design and implementation of traffic learning model**
   The internet traffic data learning model described herein considers the stochastic nature of the internet traffic data. Therefore, in its uniqueness it is not limited to working with the data from the case study only. It can—with very few modifications—be implemented in other networks.

2. **The development of the data driven bandwidth allocation algorithm**
   The bandwidth allocation algorithm suggested and developed in this work relied on the results obtained from learning the traffic data, and forecasting some of the data against what was produced. This led to a the considerations of setting the mean the predictions at one subnetwork against others as the measure of the amount of bandwidth to be allocated.

6.2 Challenges and Limitations

(i) The challenge in proving that the throughput of the network was improved by employing the algorithms developed in this work. To prove that throughput would improve, this work required feeding the network implemented in NS3 with the data with which the models were developed from. Having spent little time with NS3 and NS3 being the discrete event simulation software, it was not possible to feed in the data and compare between the outputs. However, the network topology was implemented in NS3 for anyone in need of investigating this to do just that.

(ii) Vendor specific operations: There are different network equipment vendors in the market. This limits the development of tools that address configurations for each vendor. There-

fore, this work being one of those whose end product is associated with interactions with the configurations in the network equipment, it becomes difficult to implement in environments that would contain the equipment from different vendors.

6.3 Conclusion and Recommendation

6.3.1 Conclusion

The implementation of any kind of network should consider the Quality of Experience with which the users will be provided. One way to look at it from the engineering point of view is to analyze the QoS of the network by considering throughput, packet delays and delay jitters in a timely manner. Employing the network administrators is still what is being done to optimize the QoS. Hence, any changes made to the network—despite being necessary—aren't done in a timely manner.

Therefore, throughout this report, the potential of employing machines (servers)—ML—for the dynamic allocation of bandwidth has been discussed in details while proposing the need for having a one stop point for all the network elements configurations—SDN. Hence, "IP Networks QoS Optimization Using ML Powered SDN" remains an important work that will solve most of the associated problems in network resources allocation.

6.3.2 Recommendations

Throughout this work, there have been a number of technologies that have been discussed. These technologies are not available for a student reach if one focuses on only what is being taught in class. Therefore, it is my advice that:

1. Machine Learning should be taught in the early days of the TE course (2^{nd} year should be fine)
2. Algorithms and Algorithmic Complexities should be made as one of the optional courses and taught with respect to real computing problems, and
3. The students should be exposed to computer networking research area in the early days of computer networking courses.

It is also necessary to note that this work sets the foundation on which other projects could come from. With respect to the limitations addressed, the following would make better project ideas:

1. The investigation of throughput of the network in a data driven bandwidth allocation should be of utmost importance.

2. The development of the middleware to address the associated complexity with the configuration of equipment from different vendors.

3. The investigation and analysis of traffic shapers and traffic schedulers limitations in data driven bandwidth allocation algorithm performance.

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Appendices

Appendix A

UDSM LAN Topology Implementation Code

```
// C++ specific libraries:
#include <string>

#include "ns3/core-module.h"
#include "ns3/network-module.h"
#include "ns3/internet-module.h"
#include "ns3/point-to-point-module.h"

using namespace ns3;

int main (int argc, char *argv[]){

  // Declare some constants
  const int ROUTERS = 3;
  const int DISTRIBUTION_SWITCHES = 5;
  const int ACCESS_SWITCHES = 6;

  // Create the Network nodes
  NodeContainer routers, distribution_switches, access_switches;

  routers.Create(ROUTERS);
  distribution_switches.Create(DISTRIBUTION_SWITCHES);
  access_switches.Create(ACCESS_SWITCHES);

  // Install the internet stack on each network node above
  InternetStackHelper stack;
  stack.Install(routers);
  stack.Install(distribution_switches);
  stack.Install(access_switches);

  // Create a point-to-point helper
```

```
32 PointToPointHelper p2p;
33
34 // Create an address helper
35 Ipv4AddressHelper address;
36
37 // Create the node containers for the subnets
38 NodeContainer subnet1;
39 NodeContainer subnet2, subnet3, subnet4;
40 NodeContainer subnet5, subnet6, subnet7;
41 NodeContainer subnet20, subnet30, subnet40, subnet50, subnet60,
    subnet70;
42
43 // Subnet 1 Configuration
44 subnet1.Add(routers.Get(0));
45 subnet1.Add(distribution_switches.Get(0));
46
47 NetDeviceContainer subnet1Devices = p2p.Install(subnet1);
48
49 address.SetBase("10.1.1.0", "255.255.255.0");
50
51 Ipv4InterfaceContainer subnet1Interfaces = address.Assign(
    subnet1Devices);
52
53
54 // Subnet 2 Configuration
55 subnet2.Add(distribution_switches.Get(0));
56 subnet2.Add(distribution_switches.Get(1));
57 NetDeviceContainer subnet2Devices = p2p.Install(subnet2);
58 address.SetBase("10.1.2.0", "255.255.255.0");
59 Ipv4InterfaceContainer subnet2Interfaces = address.Assign(
    subnet2Devices);
60
61 // Subnet 20 Configuration
62 subnet20.Add(distribution_switches.Get(1));
```

```
63  subnet20.Add(access_switches.Get(0));
64  NetDeviceContainer subnet20Devices = p2p.Install(subnet20);
65  address.SetBase("10.1.20.0", "255.255.255.0");
66  Ipv4InterfaceContainer subnet20Interfaces = address.Assign(
     subnet20Devices);
67
68
69  // Subnet 3 Configuration
70  subnet3.Add(distribution_switches.Get(0));
71  subnet3.Add(distribution_switches.Get(2));
72  NetDeviceContainer subnet3Devices = p2p.Install(subnet3);
73  address.SetBase("10.1.3.0", "255.255.255.0");
74  Ipv4InterfaceContainer subnet3Interfaces = address.Assign(
     subnet3Devices);
75
76  // Subnet 30 Configuration
77  subnet30.Add(distribution_switches.Get(2));
78  subnet30.Add(access_switches.Get(1));
79  NetDeviceContainer subnet30Devices = p2p.Install(subnet30);
80  address.SetBase("10.1.30.0", "255.255.255.0");
81  Ipv4InterfaceContainer subnet30Interfaces = address.Assign(
     subnet30Devices);
82
83  // Subnet 4 Configuration
84  subnet4.Add(distribution_switches.Get(0));
85  subnet4.Add(distribution_switches.Get(3));
86  NetDeviceContainer subnet4Devices = p2p.Install(subnet4);
87  address.SetBase("10.1.4.0", "255.255.255.0");
88  Ipv4InterfaceContainer subnet4Interfaces = address.Assign(
     subnet4Devices);
89
90  // Subnet 40 Configuration
91  subnet40.Add(distribution_switches.Get(3));
92  subnet40.Add(access_switches.Get(2));
```

```
93  NetDeviceContainer subnet40Devices = p2p.Install(subnet40);
94  address.SetBase("10.1.40.0", "255.255.255.0");
95  Ipv4InterfaceContainer subnet40Interfaces = address.Assign(
     subnet40Devices);
96
97  // Subnet 5 Configuration
98  subnet5.Add(distribution_switches.Get(0));
99  subnet5.Add(distribution_switches.Get(4));
100 NetDeviceContainer subnet5Devices = p2p.Install(subnet5);
101 address.SetBase("10.1.5.0", "255.255.255.0");
102 Ipv4InterfaceContainer subnet5Interfaces = address.Assign(
     subnet5Devices);
103
104 // Subnet 50 Configuration
105 subnet50.Add(distribution_switches.Get(4));
106 subnet50.Add(access_switches.Get(3));
107 NetDeviceContainer subnet50Devices = p2p.Install(subnet50);
108 address.SetBase("10.1.50.0", "255.255.255.0");
109 Ipv4InterfaceContainer subnet50Interfaces = address.Assign(
     subnet50Devices);
110
111 // Subnet 6 Configuration
112 subnet6.Add(distribution_switches.Get(0));
113 subnet6.Add(distribution_switches.Get(5));
114 NetDeviceContainer subnet6Devices = p2p.Install(subnet6);
115 address.SetBase("10.1.6.0", "255.255.255.0");
116 Ipv4InterfaceContainer subnet6Interfaces = address.Assign(
     subnet6Devices);
117
118 // Subnet 60 Configuration
119 subnet60.Add(distribution_switches.Get(5));
120 subnet60.Add(access_switches.Get(4));
121 NetDeviceContainer subnet60Devices = p2p.Install(subnet60);
122 address.SetBase("10.1.60.0", "255.255.255.0");
```

```
123   Ipv4InterfaceContainer subnet60Interfaces = address.Assign(
       subnet60Devices);
124
125   // Subnet 7 Configuration
126   subnet7.Add(distribution_switches.Get(0));
127   subnet7.Add(distribution_switches.Get(6));
128   NetDeviceContainer subnet7Devices = p2p.Install(subnet7);
129   address.SetBase("10.1.7.0", "255.255.255.0");
130   Ipv4InterfaceContainer subnet7Interfaces = address.Assign(
       subnet7Devices);
131
132   // Subnet 70 Configuration
133   subnet70.Add(distribution_switches.Get(6));
134   subnet70.Add(access_switches.Get(5));
135   NetDeviceContainer subnet70Devices = p2p.Install(subnet70);
136   address.SetBase("10.1.70.0", "255.255.255.0");
137   Ipv4InterfaceContainer subnet70Interfaces = address.Assign(
       subnet70Devices);
138
139
140   // Run the simulator
141   Simulator::Run();
142   Simulator::Destroy();
143
144   return 0;
145 }
```

Appendix B

Traffic Data Generation and Cleaning Code

```
import numpy as np
import pandas as pd
from datetime import datetime
import time
import csv


def data_generator():
    """
    This function specifically generates some data points for
   processing

    Some generalized considerations:
        Average delay = 350ms; hence a delay between 250 and 400
        Average flows = 19.9k/s; hence 19k abd 25k

    """
    start = time.time()
    start_time = []
    transmission_duration = []
    packets = []

    i = 0
    while (time.time() - start) < 300:
        start_time.append(datetime.now())
        packets.append(np.random.randint(19000, 25000))
        transmission_time = 0.001*np.random.randint(250, 400)
        time.sleep(transmission_time)
        transmission_duration.append(transmission_time)
        i += 1

```

```
    print("Generated " + str(i) + " data points")
    return zip(start_time, transmission_duration, packets)


def save_data(to_file_name, data_to_save):
    with open(to_file_name, "w", newline='') as csv_file:
        file_headers = ["Start_Time", "Transmission_Duration", "
    Packets"]
        writer = csv.DictWriter(csv_file, fieldnames=file_headers)
        writer.writeheader()

    for start_time, transmission_duration, packets in data_to_save:
        writer.writerow({"Start_Time": start_time,
                         "Transmission_Duration":
    transmission_duration,
                         "Packets": packets})


def clean_data(from_file_name, to_file_name):
    data_to_clean = pd.read_csv(from_file_name)["Packets"]
    print(data_to_clean.head())

    with open(to_file_name, 'w') as csv_file:
        file_headers = ["packets_1", "packets_2", "packets_3", "
    packets_4"]
        writer = csv.DictWriter(csv_file, fieldnames=file_headers)
        writer.writeheader()

    for index in range(0, (len(data_to_clean)-3)):
        writer.writerow({"packets_1": data_to_clean[index], "
    packets_2": data_to_clean[index+1],
                         "packets_3": data_to_clean[index+2], "
    packets_4": data_to_clean[index+3]})
        index += 1
```

```
60
61
62 # Main Program Operations
63 save_data(data_generator(), "generated_data.csv")
64 clean_data("generated_data.csv", "generated_clean_data.csv")
65
66
67
```

Appendix C

Traffic Data Learning, Prediction, and Visualization Code

```
import pandas as pd
from patsy import dmatrices
import numpy as np
import statsmodels.api as sm
import matplotlib.pyplot as plt
import time


# Create a pandas DataFrame for the counts data set.
df = pd.read_csv('clean_data.csv', header=0, infer_datetime_format=
    True)

print(df.head())
print(df.index)

time.sleep(30)


# Create the training and testing data sets.
mask = np.random.rand(len(df)) < 0.8
df_train = df[mask]
df_test = df[~mask]
print('Training data set length='+str(len(df_train)))
print('Testing data set length='+str(len(df_test)))

print(df_train.head())
print(df_test.head())


# Setup the regression expression in patsy notation. We are telling
    patsy that packets_4 is our dependent variable and
```

```
# it depends on the regression variables: packets_1, packets_2, and
    packets_3.
expr = """packets_4 ~ packets_1 + packets_2 + packets_3"""

# Set up the X and y matrices
y_train, X_train = dmatrices(expr, df_train, return_type='dataframe'
    )
y_test, X_test = dmatrices(expr, df_test, return_type='dataframe')

# Using the statsmodels GLM class, train the Poisson regression
    model on the training data set.
poisson_training_results = sm.GLM(y_train, X_train, family=sm.
    families.Poisson()).fit()

# Print the training summary.
print(poisson_training_results.summary())

# Make some predictions on the test data set.
poisson_predictions = poisson_training_results.get_prediction(X_test
    )

# .summary_frame() returns a pandas DataFrame
predictions_summary_frame = poisson_predictions.summary_frame()
print(predictions_summary_frame)

predicted_traffic= predictions_summary_frame['mean']
actual_traffic = y_test['packets_4']

# Plot the predicted traffic versus the actual traffic for the test
    data.
fig = plt.figure()
fig.suptitle('Predicted versus Actual traffic')
predicted, = plt.plot(X_test.index, predicted_traffic, 'go-', label=
    'Predicted Traffic')
```

```
actual, = plt.plot(X_test.index, actual_traffic, 'ro-', label='
    Actual Traffic')
plt.legend(handles=[predicted, actual])
plt.savefig("predict_actual.png")
plt.show()

# Show scatter plot of Actual versus Predicted Traffic
plt.clf()
fig = plt.figure()
fig.suptitle('Scatter plot of Actual versus Predicted counts')
plt.scatter(x=predicted_traffic, y=actual_traffic, marker='.')
plt.xlabel('Predicted counts')
plt.ylabel('Actual counts')
plt.savefig("predict_scatter.png")
plt.show()


```

Appendix D

Project Budget for Semester II

S/N	Item	Cost (TShs.)
1	Internet	150,000
2	Stationery	50,000
3	Emergency	20,000
	Total	220,000