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Increasing Revenue by Applying Machine Learning to Congestion Management in SDN

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Associate Professor

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1. Abstract

With the advent of 5G, IoT and 4k videos, online gaming, movie streaming and other data intensive applications, the demand for data is sky rocketing. Due to this surge in data, the load on the network increases. This heightened network load causes degradation in network performance. Which can lead to the customer Service Provider (CSP)s loosing revenue if the Service Level Agreement (SLA) are not met.

This report describes how machine learning techniques such as tit for tat can be applied to telecom networks. Machine learning applied to telecom networks help detect congestion and maintain SLAs while increasing yield (revenue).

Several experiments are run with varying conditions on the network, such as low, medium and high loads; different levels of SLA for bandwidth and delay. Once the original conditions are tested without applying any smart blocking techniques, machine learning is applied to detect congestion in the network and block flows to maintain SLA and increase the number of flows that generate revenue.

2. Literature Review

The 5G system would increase the traffic volumes by at least a 100-fold (Olwal et al., 2016) with varying use of the network and QoS of multimedia applications. It is expected that the internet download speeds for each user would be a hundred Mbps and there would be about a hundred billion devices connected to the network (Olwal et al., 2016).

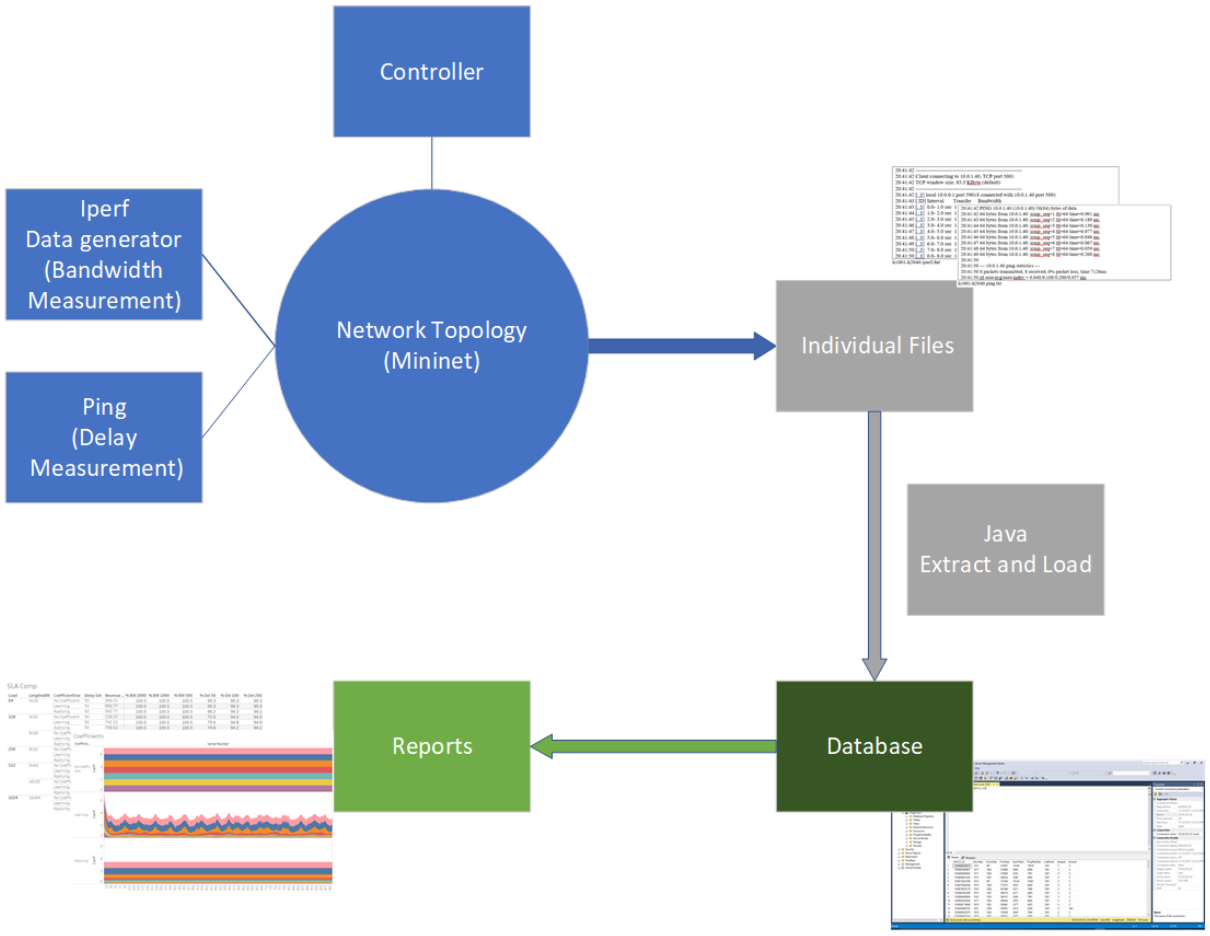
Video is one of the major bandwidth (Chen et al., 2014) utilizing application in the network. Dropping low priority packets prove to provide a better-Quality experience (Caenegem et al., 2008) to customers as in case of videos, which are the major bandwidth utilizers in the network. Caenegem et al. use an algorithm to assign priorities to packets based on the content i.e. packets containing video information would be considered more important than others like image data in the video stream. By using this approach, they were able to obtain better Quality of experience.

Congestion control is one of the poor performing areas (Sharma & Kumar, 2016) in ad-hoc wireless mobile communication systems. With growing traffic, the delay increases and there is a significant increase in the number of packets dropped (Sharma & Kumar, 2016), which leads to a poor QoS.

Performance analysis of delay and latency (Sadeghi & Barati, 2012) is a critical aspect for providing a good QoS. Sadeghi & Barati compare the network queueing performance based on Poisson distribution and Exponential distribution on OPNET (a simulation tool). It was observed that queuing the traffic in an exponential distribution proved to provide better QoS (Sadeghi & Barati, 2012) than letting the traffic flow in a normal fashion. It is expected that routing the traffic according to an exponential distribution should provide a better performance as well.

3. Architecture

The following diagram shows the process flow of the experiments, data collection and analysis involved in this report. It consists of experiment components i.e. the network, the controller and the tools used (Iperf and ping) showed in blue. While the transition phase of data collection and storing is showed in grey. The analysis phase is shown in green.



```
20:41:42 ------------------------------------------------------------
20:41:42 Client connecting to 10.0.1.40, TCP port 5001
20:41:42 TCP window size: 85.3 KByte (default)
20:41:42 ------------------------------------------------------------
20:41:42 [ 3] local 10.0.0.1 port 59018 connected with 10.0.1.40 port 5001
20:41:43 [ ID] Interval       Transfer     Bandwidth
20:41:43 [ 3]  0.0- 1.0 sec  1
20:41:44 [ 3]  1.0- 2.0 sec  1
20:41:45 [ 3]  2.0- 3.0 sec  1
20:41:46 [ 3]  3.0- 4.0 sec  1
20:41:47 [ 3]  4.0- 5.0 sec  1
20:41:48 [ 3]  5.0- 6.0 sec  1
20:41:49 [ 3]  6.0- 7.0 sec  1
20:41:50 [ 3]  7.0- 8.0 sec  1
20:41:50 [ 3]  0.0- 8.0 sec  1
h1001-h2040.iperf.dat
```

```
20:41:42 PING 10.0.1.40 (10.0.1.40) 56(84) bytes of data.
20:41:42 64 bytes from 10.0.1.40: icmp_seq=1 ttl=64 time=0.091 ms
20:41:43 64 bytes from 10.0.1.40: icmp_seq=2 ttl=64 time=0.189 ms
20:41:44 64 bytes from 10.0.1.40: icmp_seq=3 ttl=64 time=0.139 ms
20:41:45 64 bytes from 10.0.1.40: icmp_seq=4 ttl=64 time=0.077 ms
20:41:46 64 bytes from 10.0.1.40: icmp_seq=5 ttl=64 time=0.048 ms
20:41:47 64 bytes from 10.0.1.40: icmp_seq=6 ttl=64 time=0.067 ms
20:41:48 64 bytes from 10.0.1.40: icmp_seq=7 ttl=64 time=0.059 ms
20:41:49 64 bytes from 10.0.1.40: icmp_seq=8 ttl=64 time=0.200 ms
20:41:50
20:41:50 --- 10.0.1.40 ping statistics ---
20:41:50 8 packets transmitted, 8 received, 0% packet loss, time 7126ms
20:41:50 rtt min/avg/max/mdev = 0.048/0.108/0.200/0.057 ms
h1001-h2040.ping.txt
```

Figure 1: Architecture diagram

The test is performed on a virtual Software Defined Network (SDN) topology created on Mininet. Working with POX controller set to make the switches work as Layer 2 forwarding devices.

Bandwidth and delay are 2 parameters taken into consideration for measuring network performance SLAs. IPerf is used (between two randomly selected hosts) to generate random data with varying loads in the network and measure the bandwidth. While ping is used to measure the delay in between the same two nodes (as were selected for IPerf) in the network.

3.1.Mininet

Mininet is useful for interactive development, testing, and demos, especially those using OpenFlow and SDN. OpenFlow-based network controllers prototyped in Mininet can usually be transferred to hardware with minimal changes for full line-rate execution.

Mininet creates a realistic virtual network, running real kernel, switch and application code, on a single machine (VM, cloud or native), in seconds, with a single command.

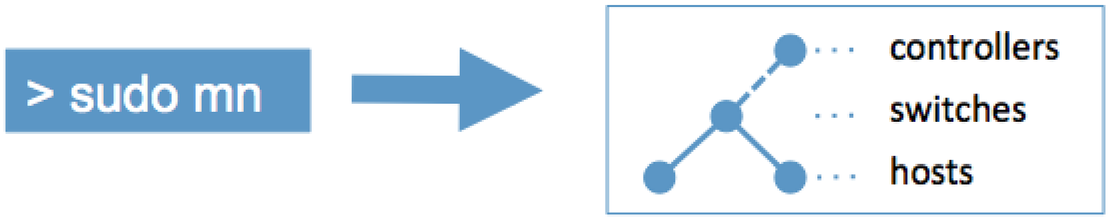


Figure 2: Mininet

3.2.POX SDN Controller

POX Controller is a simple python based open flow controller. It comes as the default controller for Mininet. Its main advantage is that it is simple and light weight. Implying it is not very useful for complex packet processing.

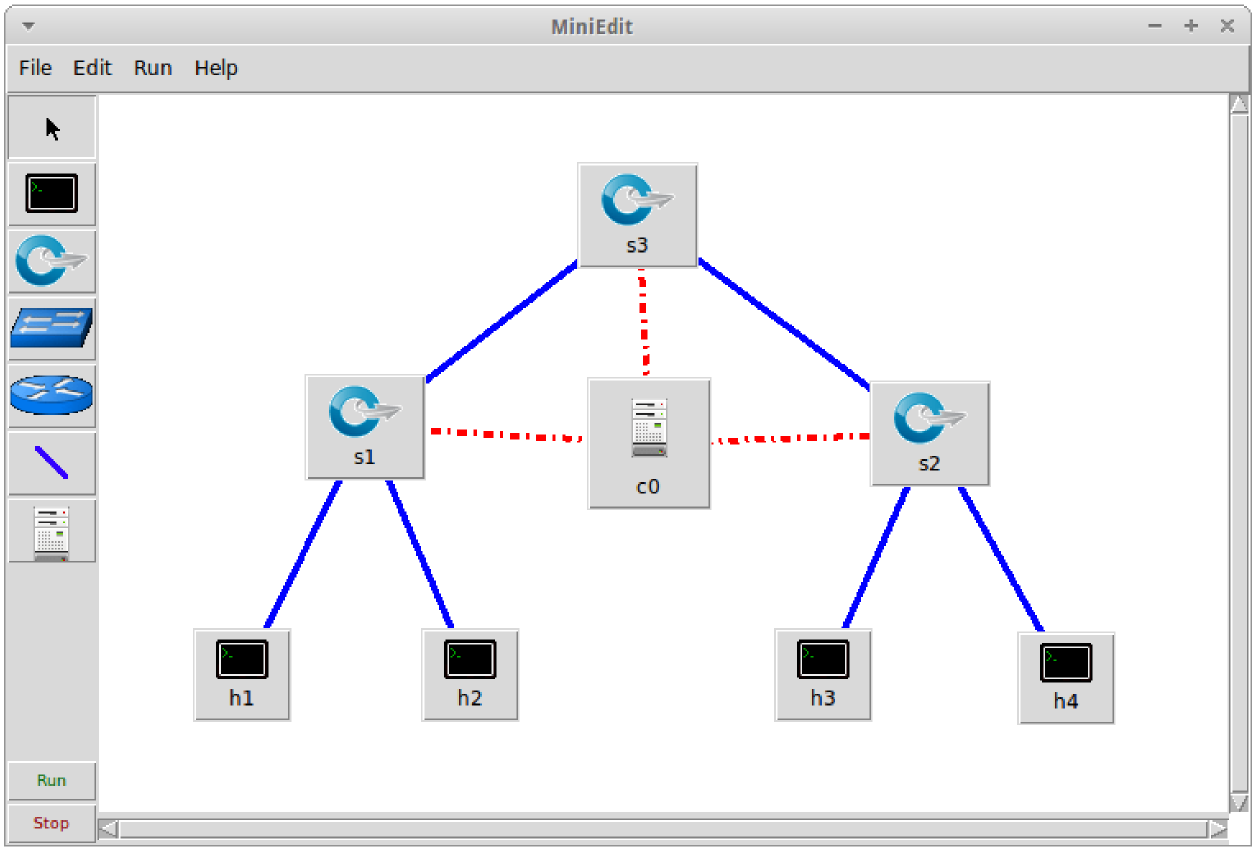


Figure 3: POX SDN Controller

POX started life as an OpenFlow controller, but can now also function as an OpenFlow switch, and can be useful for writing networking software

in general. POX officially requires Python 2.7 (though much of it will work fine with Python 2.6), and should run under Linux, Mac OS, and Windows.

3.3.IPerf

IPerf is a tool to determine the maximum bandwidth that can be achieved in between two devices. It can generate pseudo random data at a given rate and test for bandwidth.

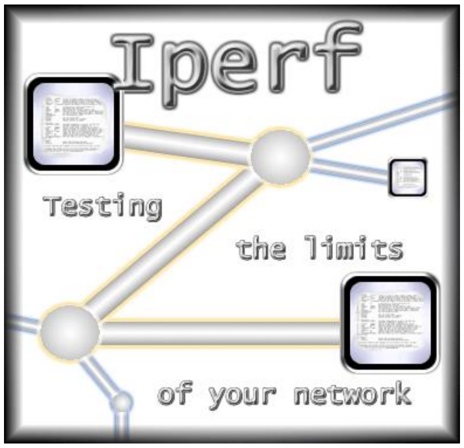


Figure 4: Iperf

It supports tuning of various parameters related to timing, buffers and protocols (TCP, UDP, SCTP with IPv4 and IPv6). For each test it reports the bandwidth, loss, and other parameters.

3.4. Network Topology

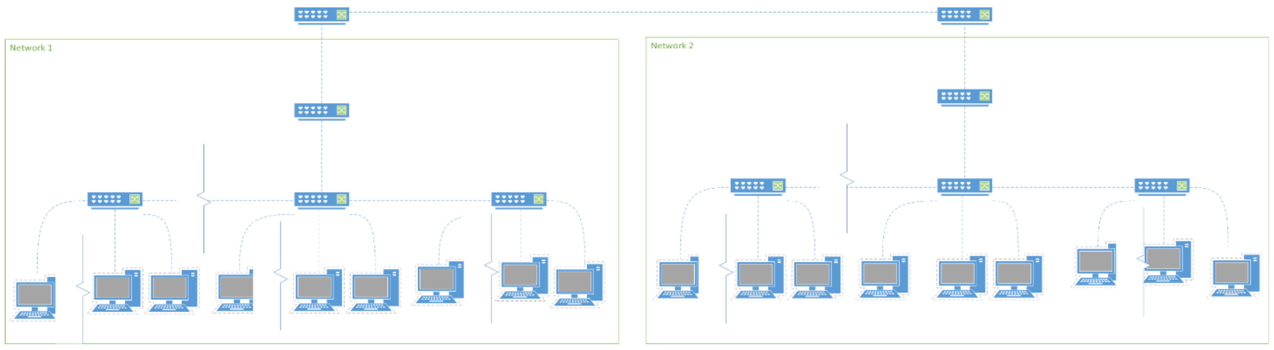


Figure 5: Virtual network topology

Distributed hybrid tree- The virtual topology is built with 2 central routers (currently working as just Layer 2 devices) connected to each other. Which are in turn connected to a central switch each. Each of the central switches are in turn connected to 10 other switches. And each switch is connected to 16 hosts. Thus, creating a sub-network of 160 hosts on each side of the network (subnet). Totaling up to 320 hosts in the entire network.

The choice of the network is based on creating a balanced network with sufficient hosts to generate enough load in the network.

4. Methodology

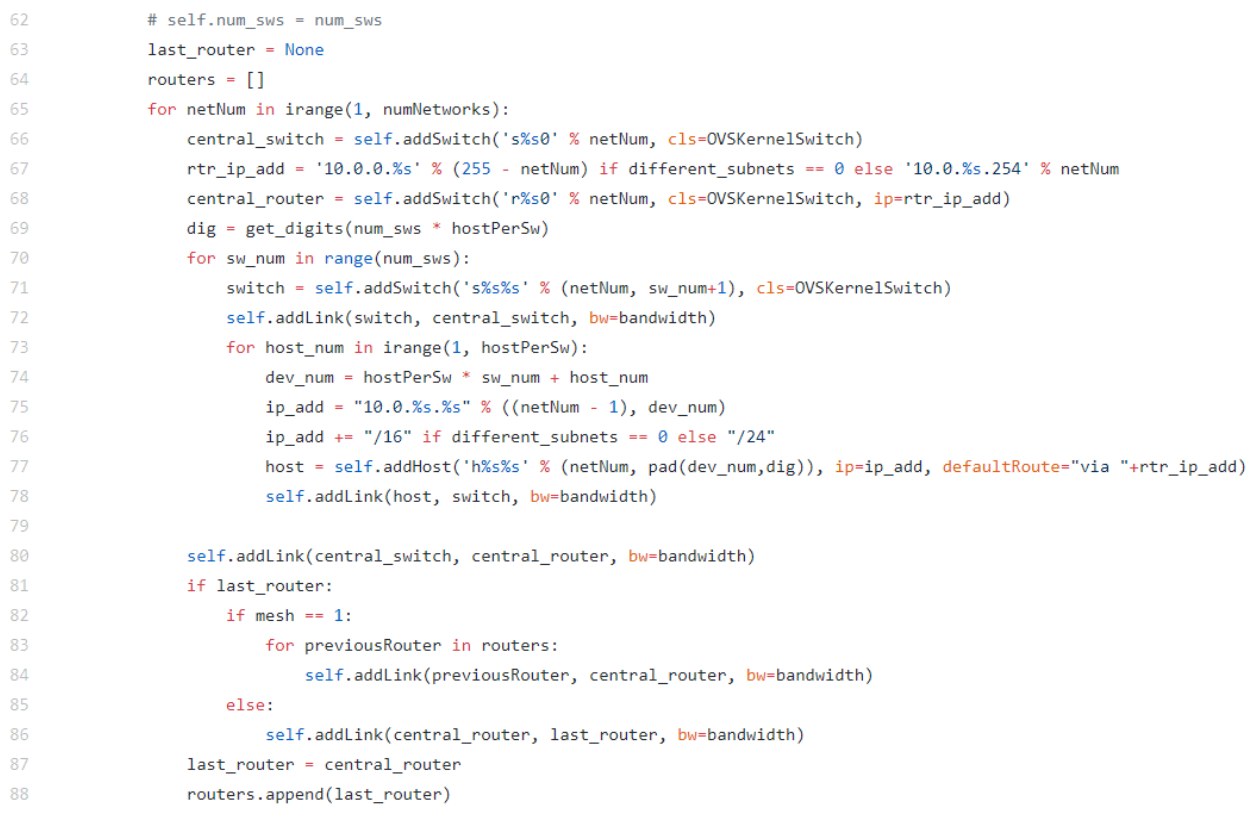
The test is performed by generating flows that would generate load on the network to purposely degrade network performance. If there are flows that do not meet the SLA, flows would start to begin getting blocked. Thus, clearing up the network for successive flows to meet the SLA. Once flows start meeting the SLA, more flows would be generated, keeping a balance of flows meeting the SLA.

A coefficient is used in this algorithm for generating flows. The value of the coefficient is used in a probabilistic approach to generate a flow. A flow will probably be generated based on the value of the coefficient as the probability of generating the flow.

4.1.Creating a topology

A virtual topology is created in Mininet using the Mininet.Topo class as a skeleton. On which various network devices such as switches are added using the self.addSwitch() method. Followed by addition of links joining the switches as described in the topology section above. Based on the topology configuration chosen, switches are added, linked and configured. Varying parameters such as meshed network of switches, or different subnets in the network, number of networks will result in network topology being generated differently.

Finally, all the hosts are added. A suitable IP addressing scheme is chosen based the parameters chosen before initializing the topology. Once that is complete, the configuration and names are dumped on to the host and added to the network topology.



```
        # self.num_sws = num_sws
        last_router = None
        routers = []
        for netNum in irange(1, numNetworks):
            central_switch = self.addSwitch('s%s0' % netNum, cls=OVSKernelSwitch)
            rtr_ip_add = '10.0.0.%s' % (255 - netNum) if different_subnets == 0 else '10.0.%s.254' % netNum
            central_router = self.addSwitch('r%s0' % netNum, cls=OVSKernelSwitch, ip=rtr_ip_add)
            dig = get_digits(num_sws * hostPerSw)
            for sw_num in range(num_sws):
                switch = self.addSwitch('s%s%s' % (netNum, sw_num+1), cls=OVSKernelSwitch)
                self.addLink(switch, central_switch, bw=bandwidth)
                for host_num in irange(1, hostPerSw):
                    dev_num = hostPerSw * sw_num + host_num
                    ip_add = "10.0.%s.%s" % ((netNum - 1), dev_num)
                    ip_add += "/16" if different_subnets == 0 else "/24"
                    host = self.addHost('h%s%s' % (netNum, pad(dev_num,dig)), ip=ip_add, defaultRoute="via "+rtr_ip_add)
                    self.addLink(host, switch, bw=bandwidth)

            self.addLink(central_switch, central_router, bw=bandwidth)
            if last_router:
                if mesh == 1:
                    for previousRouter in routers:
                        self.addLink(previousRouter, central_router, bw=bandwidth)
                else:
                    self.addLink(central_router, last_router, bw=bandwidth)
            last_router = central_router
            routers.append(last_router)
```

Figure 6: Code to create topology

After the topology has been created, the network is started, and all the configurations are dumped on to the devices.

4.2.Generating flows

After a certain interval of time, a new thread is created that creates a new instance of an object and calls a function that selects 2 random hosts from the list of hosts in the network. One from the first network and the other from the 2nd. The first hosts is made a IPerf server and the other host is made as a client. This is done to stress the link between the two routers. The duration and target bandwidth is determined as the parameters while initiation of the program. Along with that ping is performed for the same durations as the IPerf.

4.3.Collecting data

The result of IPerf and ping are taken every certain interval and put into individual files along with the timestamp for the host pairs. If the hosts pair selected are h11 and h21. For IPerf the files are names as h11-h21.iperf.dat. While the files generated by ping are named as h11-h21.ping.txt. A few sample files are attached below:

Table 1: h1001-h2040.iperf.dat

```
20:41:42 ------------------------------------------------------------
20:41:42 Client connecting to 10.0.1.40, TCP port 5001
20:41:42 TCP window size: 85.3 KByte (default)
20:41:42 ------------------------------------------------------------
20:41:42 [  3] local 10.0.0.1 port 59018 connected with 10.0.1.40 port 5001
20:41:43 [ ID] Interval       Transfer     Bandwidth
20:41:43 [  3]  0.0- 1.0 sec  1.91 MBytes  16.0 Mbits/sec
20:41:44 [  3]  1.0- 2.0 sec  1.91 MBytes  16.0 Mbits/sec
20:41:45 [  3]  2.0- 3.0 sec  1.91 MBytes  16.0 Mbits/sec
20:41:46 [  3]  3.0- 4.0 sec  1.91 MBytes  16.0 Mbits/sec
20:41:47 [  3]  4.0- 5.0 sec  1.91 MBytes  16.0 Mbits/sec
20:41:48 [  3]  5.0- 6.0 sec  1.91 MBytes  16.0 Mbits/sec
20:41:49 [  3]  6.0- 7.0 sec  1.91 MBytes  16.0 Mbits/sec
20:41:50 [  3]  7.0- 8.0 sec  1.91 MBytes  16.0 Mbits/sec
20:41:50 [  3]  0.0- 8.0 sec  15.3 MBytes  16.0 Mbits/sec
```

Table 2: h1001-h2040.ping.txt

```
20:41:42 PING 10.0.1.40 (10.0.1.40) 56(84) bytes of data.
20:41:42 64 bytes from 10.0.1.40: icmp_seq=1 ttl=64 time=0.091 ms
20:41:43 64 bytes from 10.0.1.40: icmp_seq=2 ttl=64 time=0.189 ms
20:41:44 64 bytes from 10.0.1.40: icmp_seq=3 ttl=64 time=0.139 ms
20:41:45 64 bytes from 10.0.1.40: icmp_seq=4 ttl=64 time=0.077 ms
20:41:46 64 bytes from 10.0.1.40: icmp_seq=5 ttl=64 time=0.048 ms
20:41:47 64 bytes from 10.0.1.40: icmp_seq=6 ttl=64 time=0.067 ms
20:41:48 64 bytes from 10.0.1.40: icmp_seq=7 ttl=64 time=0.059 ms
20:41:49 64 bytes from 10.0.1.40: icmp_seq=8 ttl=64 time=0.200 ms
20:41:50
20:41:50 --- 10.0.1.40 ping statistics ---
20:41:50 8 packets transmitted, 8 received, 0% packet loss, time 7126ms
20:41:50 rtt min/avg/max/mdev = 0.048/0.108/0.200/0.057 ms
```

4.4.Parsing the results

Once all the data collection is complete, all the files generated are processed to extract relevant information and stored along with the exact timestamp as a list.

For example, in the first file for reading iperf.dat it will extract the host pair from the file name and store the names in memory. It will read the time data and store it in a new object created for that row, set the host pair to the host pair for that file which is in memory. Next it will extract the bandwidth and map it to the same object. It will add the object to the list and then move on to the next row.

Similarly, for the ping.txt file, it extracts the host pair from the file name. Get the timestamp and rtt from the last part and add them to a list.

4.5.Dumping to the database

Once the data is extracted, the java program when called with the command line argument of *load*, generates a unique BATCH_ID for that batch, loops through all the data that was extracted, attaches the unique BATCH_ID and prepares SQL insert statements. The statements are executed as a batch for quick loading into the database. A count of the rows inserted for each file is accumulated. At the end of the batch, the accumulated counts for each table is kept in a separate table along with the BATCH_ID to keep track of the number of rows inserted in each batch. Upon completion, the java program returns the BATCH_ID.

Each batch has a set value of link bandwidth, SLA, session parameters (duration and target bandwidth).

Once all the batches for a session are complete, they are inserted into another table called sessionmap along with the session link bandwidth, SLA, session name made from the session parameters (duration, target bandwidth) and the number of time the session ran (i.e. no coefficient, learning or applying phase).

After loading to the database, the data is normalized to the closest 1 second timestamp.

4.6.Generating graphs

The data that is loaded is normalized to a 1 second interval. This gives flexibility to compare the values in a sequential manner.

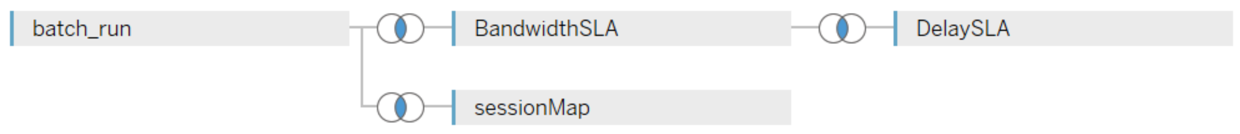


Figure 7: Joins in database for creating graphs

Views are created to get the required information from each table. Which are joint based on batch_id.

BandwdthSLA is a view that contains the max, min bandwidths, the number of flows that met 3 levels of SLA for bandwidth. Similarly, DelaySLA contains the max, min delays, the number of flows that met 3 levels of SLA for delay.

The table batch_run is populated with the number of rows inserted into each table, the number of flows dropped, and the number of flows blocked. While sessionmap contains a mapping of each batch to a session, e.g. a session might be DoubleSLA2x1000 indicating that the session was run with the SLA set to double of what was usually considered. 2 indicated that the test was run for the 2nd time i.e. the applying phase after 0 (no coefficient) and 1(learning phase). While 1000 indicated that there were 1000 flows generated in the session.

5. Experiments

The experiments were different values of intervals, bandwidth of the links, target bandwidth, durations etc.

5.1.Intervals

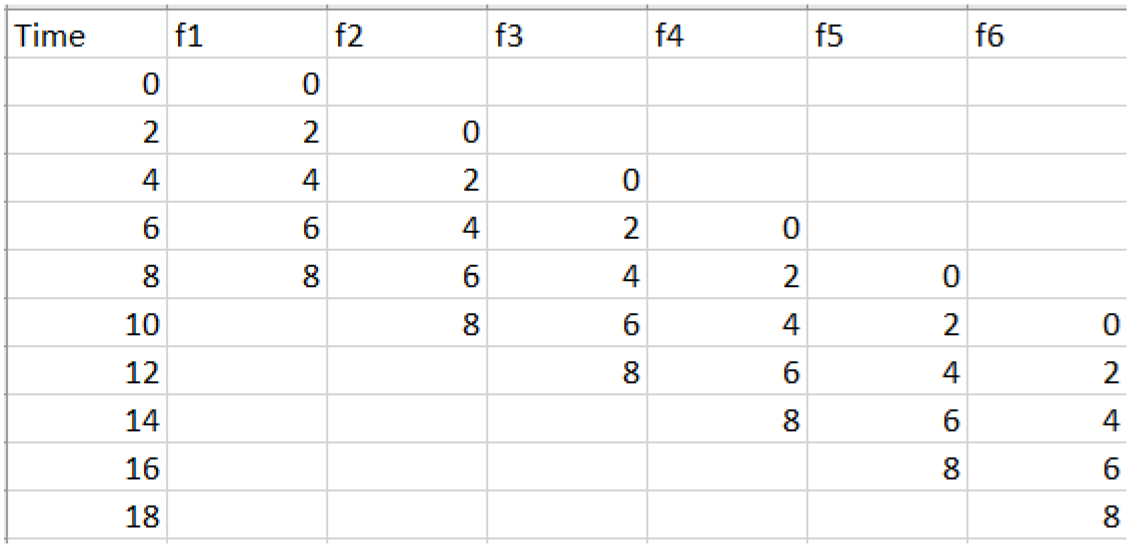
Initially it was anticipated that there might be delays in collecting metrics and the interval was set to be at 10s. Implying a new flow would be generated after 10 seconds. Network statistics would be collected every half interval time, i.e. 5 seconds.

After carefully inspecting all the data collected, it was found that the data collected was precise to 1 second (with variations in a few micro seconds). So, the interval was set to 2 seconds and the network statistics were taken every 1 second.

5.2.Duration

The tests were run with several different values for duration. Ranging from 4 to 32 seconds. Whenever a flow is generated it would be run for that amount of duration. Implying there would duration/interval amount of flows running at the same time during the entire test, except the initiation and tear down of the batch. For example, let’s say we take interval to be 2 and duration to be 8. At t=0 a new flow would be generated. After 2 seconds another flow would be generated, at t=2, taking the current number of flows to 2. Again after 2 seconds, another flow would be generated, at t=4, taking the total number of flows to 4, and so on. After the end of the 8 seconds, the first flow would be teared down, and a new flow be generated. Keeping the total number of flows to be constant at duration/interval.

Table 3: Duration of flows with time



Time	f1	f2	f3	f4	f5	f6
0	0					
2	2	0				
4	4	2	0			
6	6	4	2	0		
8	8	6	4	2	0	
10		8	6	4	2	0
12			8	6	4	2
14				8	6	4
16					8	6
18						8

5.3.Bandwidth

The target bandwidth is varied throughout the tests to generate different amounts of load in the network. Bandwidths are kept as multiples of 16 Mbits/sec. Ranging from 16 Mbits/sec to 128 Mbits/sec.

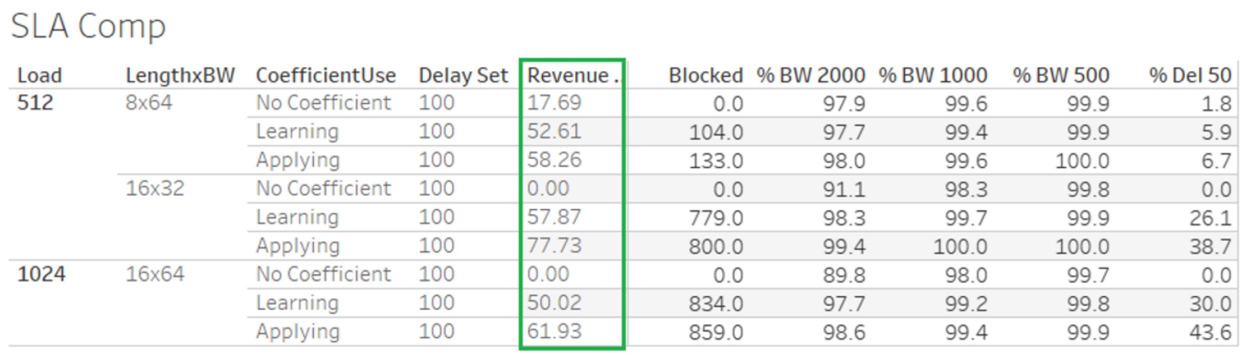
The product of duration and bandwidth gives the constant amount of load that is always present in the network.

6. Results

6.1.Revenue Increase

The following table shows the comparison for percentage of flows that meet the SLA for different load conditions along with the flows that generate revenue with the experiments being run with the SLA set to bandwidth of 1Mb/sec and delay set to 100 msec. Along with the different phases of the experiment, i.e. without any blocking coefficient, then with learning the coefficient by applying a blocking factor to decide the probability of generating the next flow and modifying the value of the coefficient based on the success of the current flow. And that being followed by the applying phase where the coefficient is fixed to a set value, which is the average value of the coefficient in the learning phase.

Table 4: SLA Comparison for high load flows



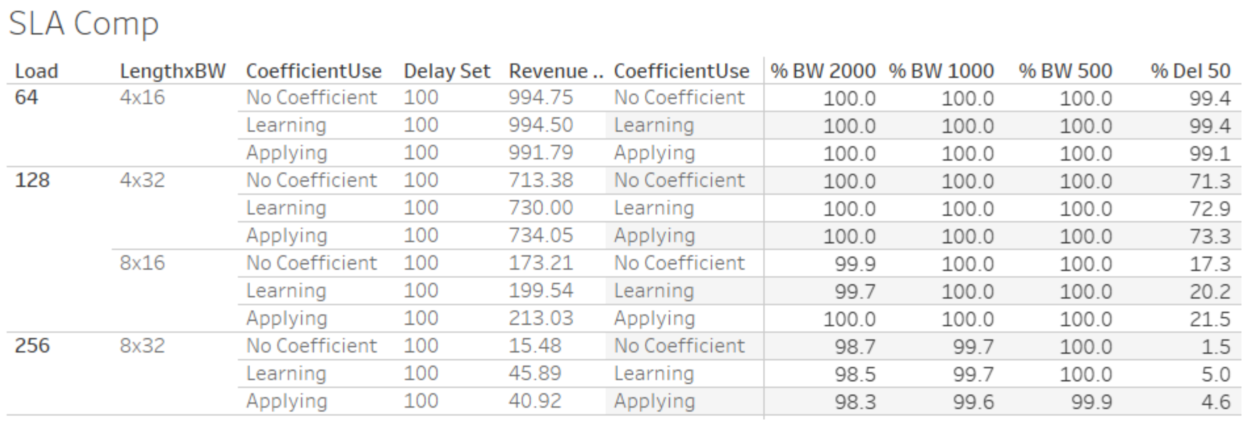
SLA Comp

Load	LengthxBW	CoefficientUse	Delay Set	Revenue .	Blocked	% BW 2000	% BW 1000	% BW 500	% Del 50
512	8x64	No Coefficient	100	17.69	0.0	97.9	99.6	99.9	1.8
		Learning	100	52.61	104.0	97.7	99.4	99.9	5.9
		Applying	100	58.26	133.0	98.0	99.6	100.0	6.7
	16x32	No Coefficient	100	0.00	0.0	91.1	98.3	99.8	0.0
		Learning	100	57.87	779.0	98.3	99.7	99.9	26.1
		Applying	100	77.73	800.0	99.4	100.0	100.0	38.7
1024	16x64	No Coefficient	100	0.00	0.0	89.8	98.0	99.7	0.0
		Learning	100	50.02	834.0	97.7	99.2	99.8	30.0
		Applying	100	61.93	859.0	98.6	99.4	99.9	43.6

As can be seen from the table above, with heavy loads having load factor of 512 Mb (8sec * 64 Mb/sec or 16sec * 32 Mb/sec) or higher, when no blocking is applied, only 17.69 generate revenue for 8x64 while no flows generate revenue for 16x32 and 16x64. After applying the machine learning technique, to learn an optimal value of the coefficient, the flows that generate revenue are increased to 52.61 (197.31%), 57.7(100%) and 50.02(100%) respectively. After applying this blocking coefficient, we see a further improvement in the flows that meet the SLA and generate revenue. The increase in the number of flows that generate revenue being 58.26 (229.33%), 77.73(100%) and 61.93(100%) respectively.

Although it works great for higher loads, it doesn't increase significant revenue with lower loads as there isn't enough congestion in the network. As can be seen in the table below which again compares the number of flows that meet the SLA for bandwidth and delay.

Table 5: SLA Comparison for low load flows



SLA Comp

Load	LengthxBW	CoefficientUse	Delay Set	Revenue ..	CoefficientUse	% BW 2000	% BW 1000	% BW 500	% Del 50
64	4x16	No Coefficient	100	994.75	No Coefficient	100.0	100.0	100.0	99.4
		Learning	100	994.50	Learning	100.0	100.0	100.0	99.4
		Applying	100	991.79	Applying	100.0	100.0	100.0	99.1
128	4x32	No Coefficient	100	713.38	No Coefficient	100.0	100.0	100.0	71.3
		Learning	100	730.00	Learning	100.0	100.0	100.0	72.9
		Applying	100	734.05	Applying	100.0	100.0	100.0	73.3
	8x16	No Coefficient	100	173.21	No Coefficient	99.9	100.0	100.0	17.3
		Learning	100	199.54	Learning	99.7	100.0	100.0	20.2
		Applying	100	213.03	Applying	100.0	100.0	100.0	21.5
256	8x32	No Coefficient	100	15.48	No Coefficient	98.7	99.7	100.0	1.5
		Learning	100	45.89	Learning	98.5	99.7	100.0	5.0
		Applying	100	40.92	Applying	98.3	99.6	99.9	4.6

From the table above, it is seen that with light loads having load factor of 64 Mb (4sec * 16 Mb/sec) the, when no blocking is applied, almost all flows meet the SLA 994.75 generate revenue. For 4x32 there are 713.38 flows that generate revenue and for 8x16 there are 173.21 flows that generate revenue. For 8x32 there are only 15.48 flows that generate revenue. After applying the machine learning technique, to learn an optimal value of the coefficient, the flows that generate decreased to 991.79(-0.02 %) while for 4x32 the flows that generate revenue increased to 730(2.33 %). While for 8x16 the flows that generate revenue increased to 199.54(15.20 %) and 40.92(196.45 %) for 8x32. After applying this blocking coefficient, we see a improvement in the flows that meet the SLA and generate revenue for 4x32 and 8x16. The increase in the number of flows that generate revenue being 734.05 (2.90 %) and 213.03 (22.99

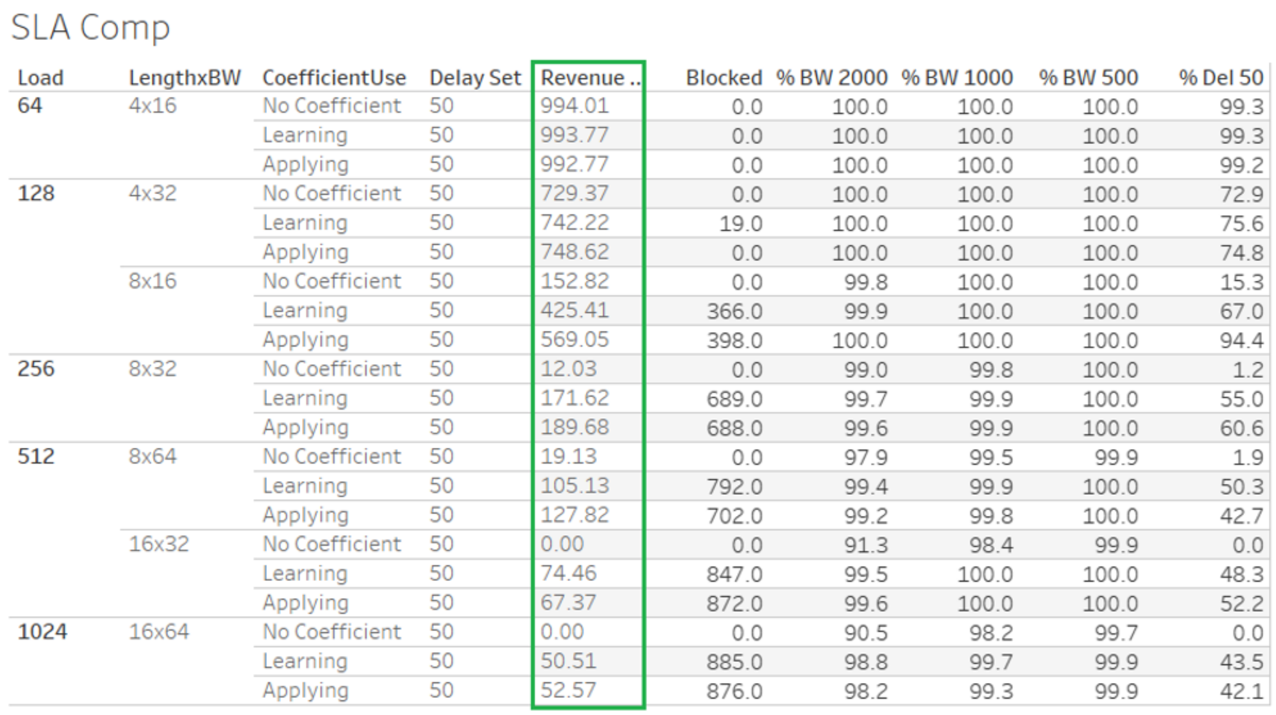
%) respectively. While for 4x16 and 8x32, it decreased from the learning phase, to 991.79(-0.30 %) for 4x16 and 40.92(164.34 %) for 8x32.

With heavy loads we see more flows meeting the SLA. After the algorithm was applied, we see a significant improvement.

6.2.Doubling SLA

Like the previous table, the following table shows the comparison for percentage of flows that meet the SLA for different load conditions along with the flows that generate revenue with the experiments being run with the SLA set to bandwidth of 1Mb/sec but the delay set to 50 msec.

Table 6: SLA Comparison for double SLA



SLA Comp

Load	LengthxBW	CoefficientUse	Delay Set	Revenue ..	Blocked	% BW 2000	% BW 1000	% BW 500	% Del 50
64	4x16	No Coefficient	50	994.01	0.0	100.0	100.0	100.0	99.3
		Learning	50	993.77	0.0	100.0	100.0	100.0	99.3
		Applying	50	992.77	0.0	100.0	100.0	100.0	99.2
128	4x32	No Coefficient	50	729.37	0.0	100.0	100.0	100.0	72.9
		Learning	50	742.22	19.0	100.0	100.0	100.0	75.6
		Applying	50	748.62	0.0	100.0	100.0	100.0	74.8
	8x16	No Coefficient	50	152.82	0.0	99.8	100.0	100.0	15.3
		Learning	50	425.41	366.0	99.9	100.0	100.0	67.0
		Applying	50	569.05	398.0	100.0	100.0	100.0	94.4
256	8x32	No Coefficient	50	12.03	0.0	99.0	99.8	100.0	1.2
		Learning	50	171.62	689.0	99.7	99.9	100.0	55.0
		Applying	50	189.68	688.0	99.6	99.9	100.0	60.6
512	8x64	No Coefficient	50	19.13	0.0	97.9	99.5	99.9	1.9
		Learning	50	105.13	792.0	99.4	99.9	100.0	50.3
		Applying	50	127.82	702.0	99.2	99.8	100.0	42.7
	16x32	No Coefficient	50	0.00	0.0	91.3	98.4	99.9	0.0
		Learning	50	74.46	847.0	99.5	100.0	100.0	48.3
		Applying	50	67.37	872.0	99.6	100.0	100.0	52.2
1024	16x64	No Coefficient	50	0.00	0.0	90.5	98.2	99.7	0.0
		Learning	50	50.51	885.0	98.8	99.7	99.9	43.5
		Applying	50	52.57	876.0	98.2	99.3	99.9	42.1

After increasing the set SLA for delay, we see similar results. The number of flows that are successful have increased significantly whenever the flows run for more than 8seconds. When the flows are run without any blocking coefficient, the number for flows that generate revenue are 994.01 for 4x16, 729.37 for 4x32, 152.82 for 8x16, 12.03 for 8x32 and 19.13 for 8x64. While for 16x32 and 16x64 there are no flows that generate revenue when no blocking is used.

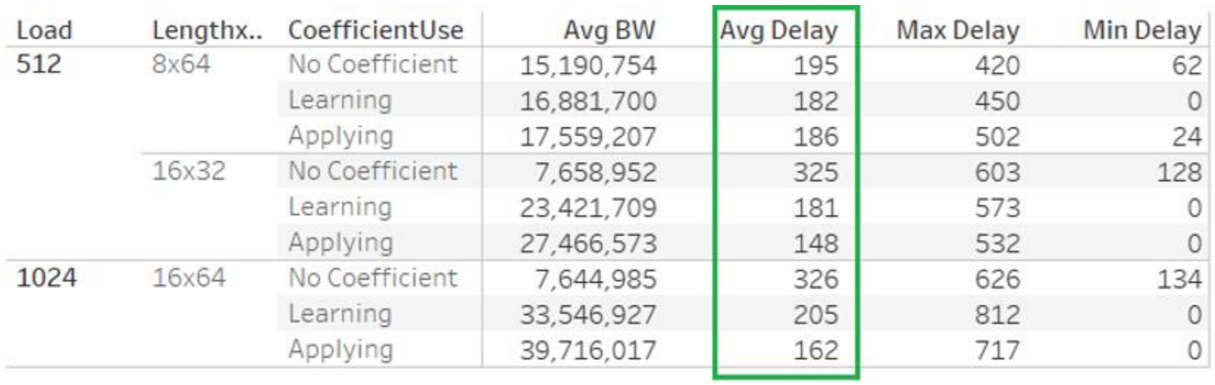
After applying the machine learning algorithm, to learn the value of the coefficient, the number of flows that generate revenue is decreased by a small fraction to 993.77(-0.02 %) for 4x16 while for the rest of the cases, the number of flows that generate revenue are increased to 742.22(1.76 %), 425.41(167.86 %), 171.62(1326.60 %), 105.13(449.56 %), 74.46(100.00 %), 50.51(100.00 %) respectively.

After applying this learned coefficient, the number of decreased for the 4x16 to 992.77(-0.12 %), while the number of flows that generate revenue for the rest of the cases increased to 748.62(2.64 %), 569.05(258.30 %), 189.68(1476.72 %), 127.82(568.17 %), 67.37(100.00 %), 52.57(100.00 %) respectively.

6.3.Delay comparison

The following table shows the comparison of average bandwidth; and minimum, average and maximum delay in the network for different cases of length and bandwidth.

Table 7: Delay comparison



Load	Lengthx..	CoefficientUse	Avg BW	Avg Delay	Max Delay	Min Delay
512	8x64	No Coefficient	15,190,754	195	420	62
		Learning	16,881,700	182	450	0
		Applying	17,559,207	186	502	24
	16x32	No Coefficient	7,658,952	325	603	128
		Learning	23,421,709	181	573	0
		Applying	27,466,573	148	532	0
1024	16x64	No Coefficient	7,644,985	326	626	134
		Learning	33,546,927	205	812	0
		Applying	39,716,017	162	717	0

As seen from the table above, the average delay has gone down with blocking in both cases of learning the coefficient and applying the value of the coefficient in the algorithm.

6.4. Coefficient Values

The following diagrams show the charts for values of coefficient for 3 different scenarios.

The first chart shows the values of coefficient stacked on top of each other for different values of length and bandwidth.

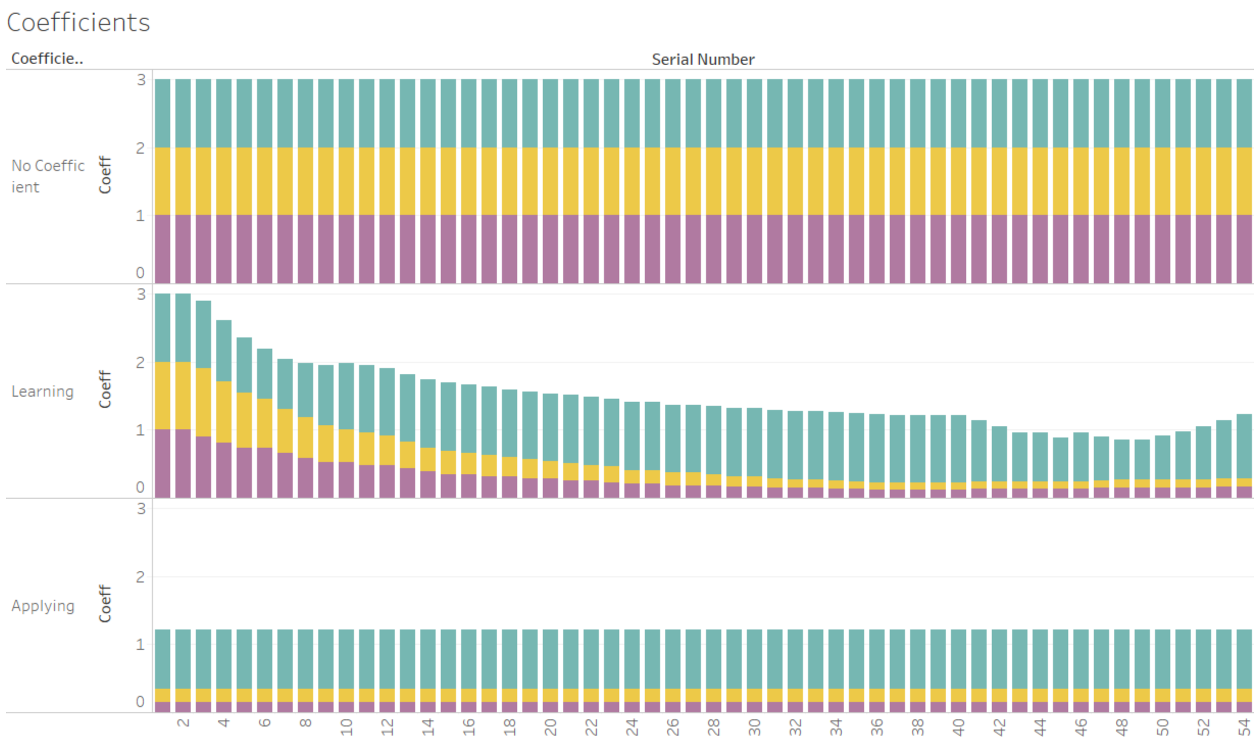


Figure 8: Graph showing value of coefficients over time

LengthxBW

🟩 8x64

🟨 16x32

🟪 16x64

This graph shows the values of the coefficients at the initial few times of the experiment being performed. Looking at the graph in the learning phase, the value of the coefficient keeps on decreasing as the load keeps on increasing over time.

However, if we look over a wide range of time as in the graph below:

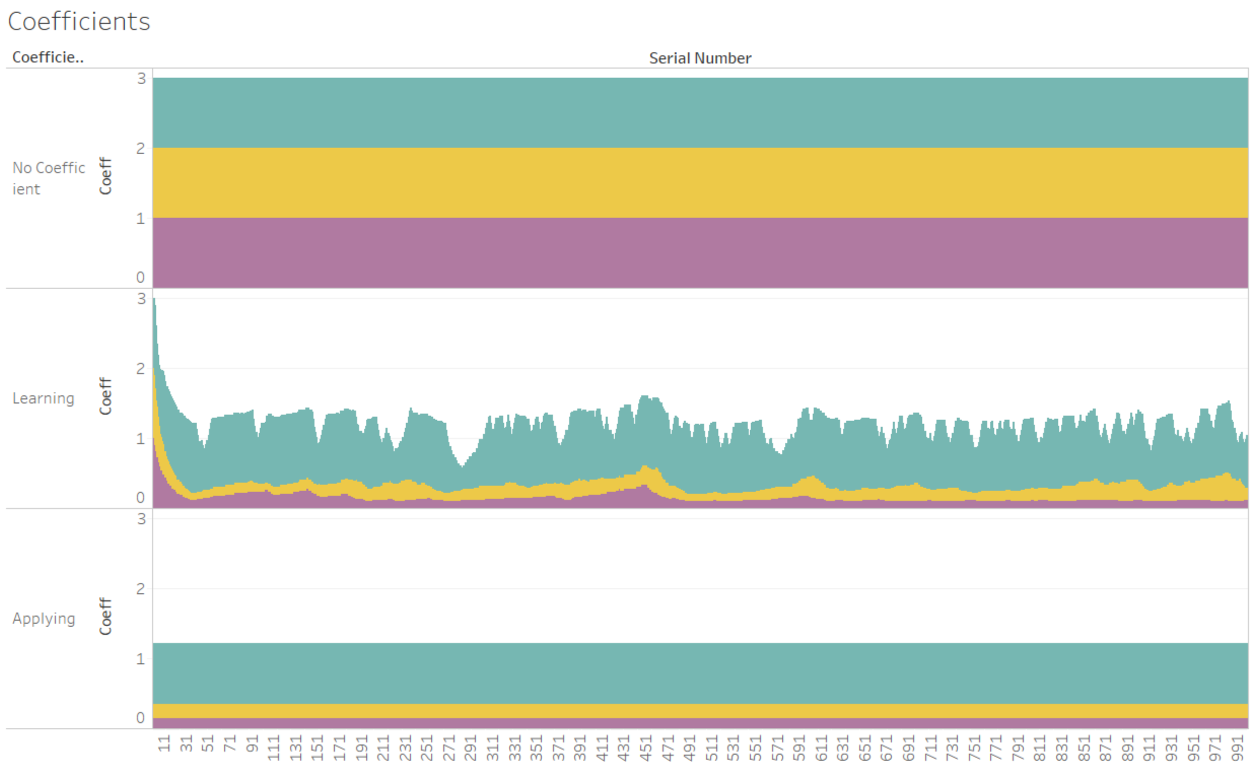


Figure 9: Graph showing value of coefficients over long range

After looking at the coefficient in the learning phase, over a wide range of time, the coefficient eventually saturates to a stable value, average of which is applied in the 3rd phase which is the applying phase. Where the average value of the coefficient from the learning phase is used as the probability of generating new flows.

For low load such as 8x64, value of the coefficient fluctuates from the mid to the higher end indicating that the network frequently changes clears up and gets blocked again.

We can see the graph as below.

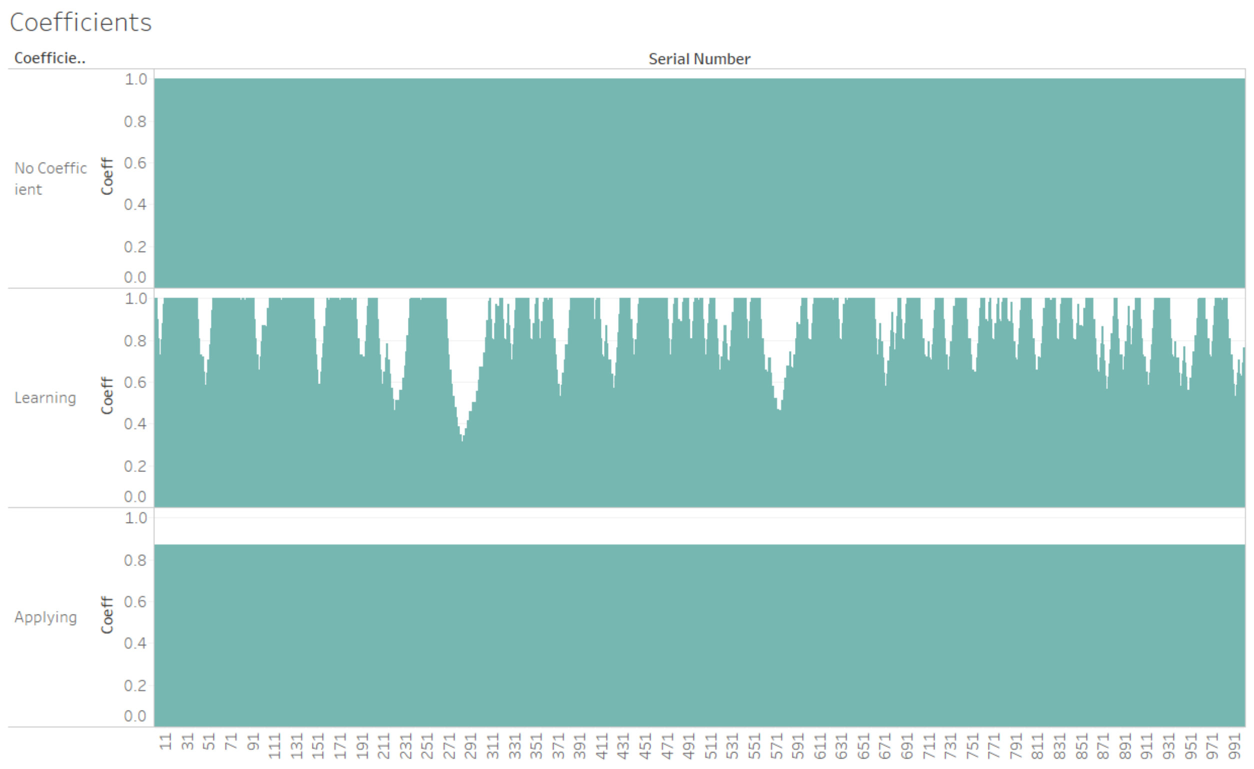


Figure 10: Graph showing value of coefficients for duration: 8sec bandwidth: 64 Mb/sec

For higher loads such as 16x32 the graph is below:

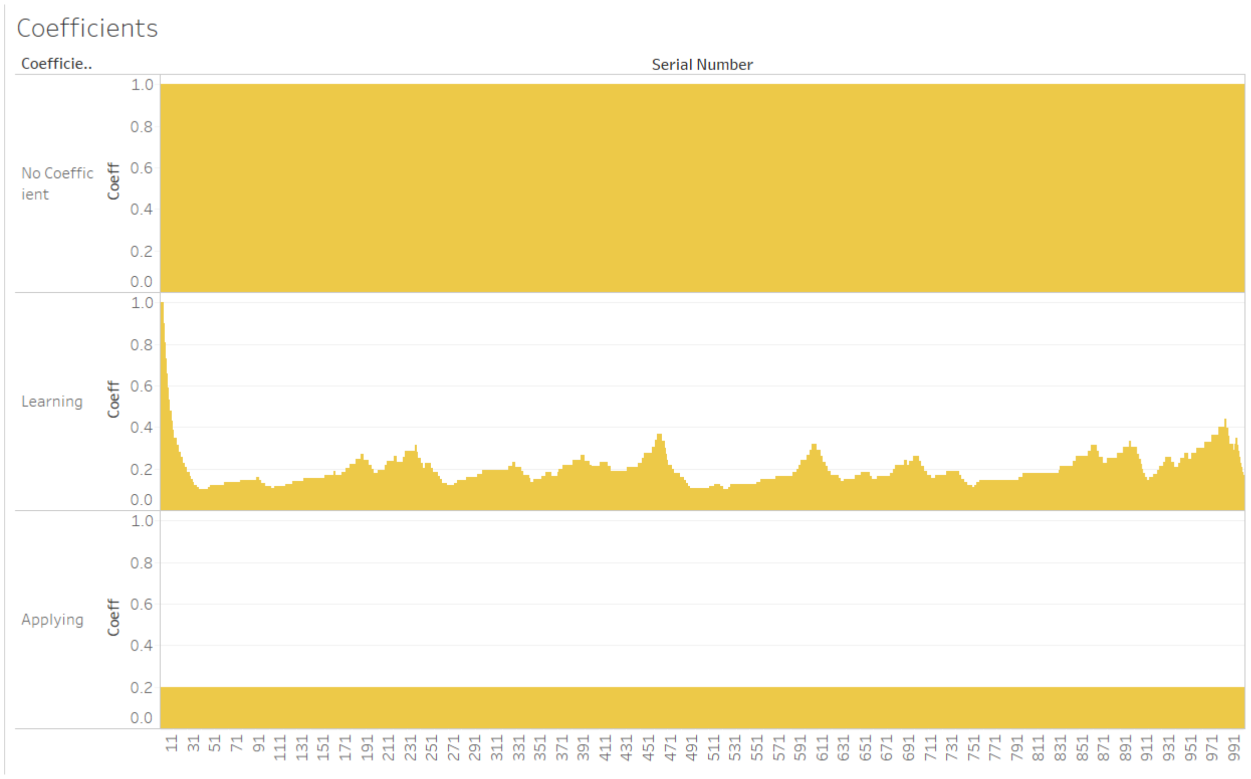


Figure 11: Graph showing value of coefficients for duration: 16sec bandwidth: 32 Mb/sec

In this case the value of the coefficients dips to a low value as there are more flows running simultaneously in the network. And as we keep blocking the flows, the value of the coefficient increases and then comes down again.

A similar case is observed for loads such as 16x64

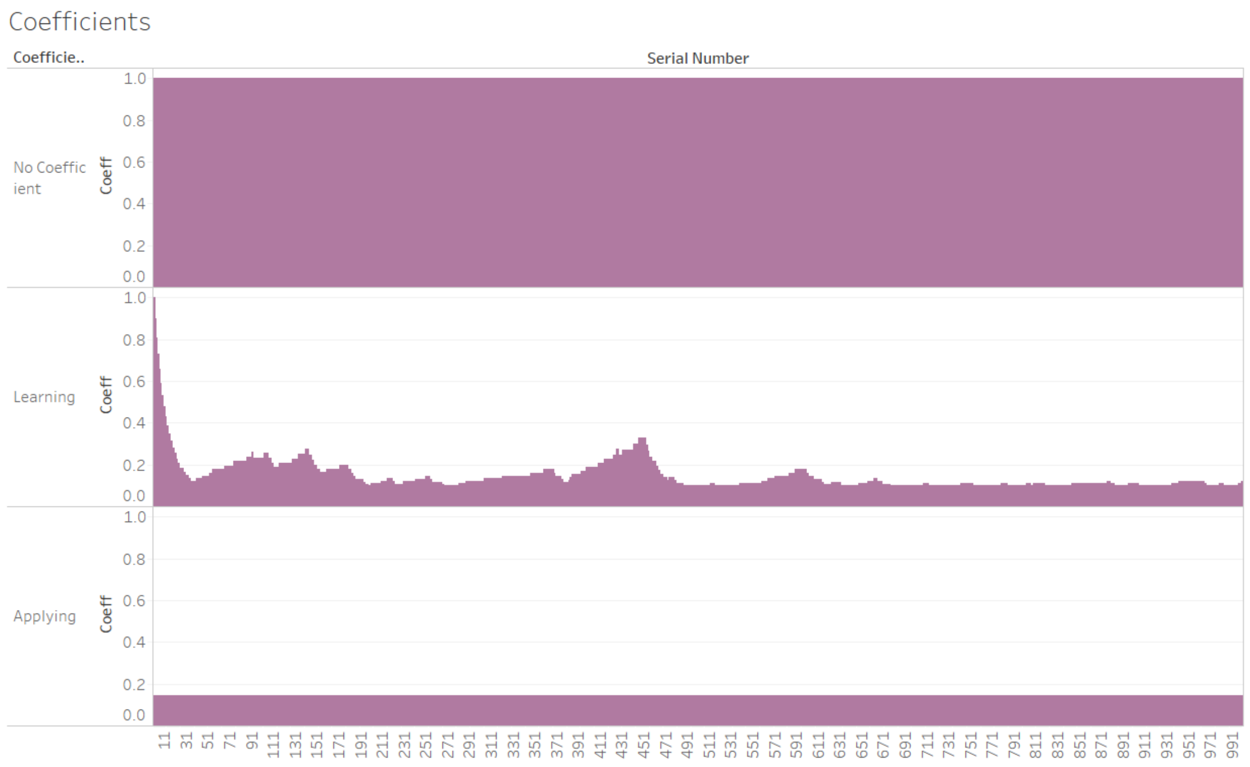
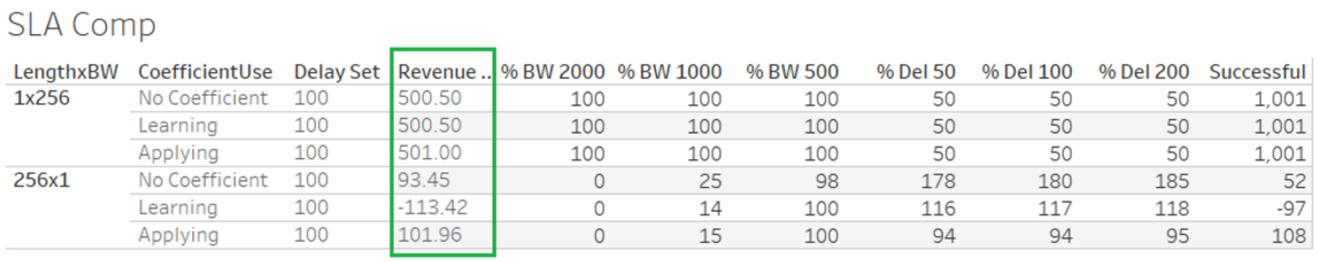


Figure 12: Graph showing value of coefficients for duration: 16sec bandwidth: 64 Mb/sec

6.5. Extreme cases

The following table shows the comparison of the number of flows that meet the SLA for bandwidth and delay for extreme cases of length and target bandwidth.



SLA Comp

LengthxBW	CoefficientUse	Delay Set	Revenue ..	% BW 2000	% BW 1000	% BW 500	% Del 50	% Del 100	% Del 200	Successful
1x256	No Coefficient	100	500.50	100	100	100	50	50	50	1,001
	Learning	100	500.50	100	100	100	50	50	50	1,001
	Applying	100	501.00	100	100	100	50	50	50	1,001
256x1	No Coefficient	100	93.45	0	25	98	178	180	185	52
	Learning	100	-113.42	0	14	100	116	117	118	-97
	Applying	100	101.96	0	15	100	94	94	95	108

When the experiment is repeated with extreme values of length and bandwidth, it is seen that the coefficient doesn’t help much.

The number of flows that generate revenue without applying blocking are 500.5 for 1x256 and 91.45 for 256x1. While learning the optimal value of the coefficient, the number of flows that generate revenue are 500.5 for 1x256 which is the same without applying any blocking. While for the 256x1 no flows generate any revenue. While applying the coefficient to the network, the number of flows that generate revenue are increased to 101.96(9.1 %) for 256x1 while it remains the same for 1x256.

It is seen that fewer the flows running simultaneously in the network with very high target bandwidth, the network performs better. Unlike in the case of very high number flows running with very low target bandwidth. In which case the network performance is completely degraded.

7. Discussion

7.1. Limitations

The experiments were performed on a Linux machine installed on a Personal Computer (PC) which have limited amount of resources at its disposal.

The database is shifted to the cloud, which does reduce the load on the computer, but still is not very efficient to handle high loads of data being generated in the virtual network.

This experiment might be run on super computers/ research computers with much higher computing capability.

7.2. Algorithm Improvements

The experiments were tested with only one strategy – tit for tat, which works in increasing revenue. But might not be the best algorithm that might be applied to increasing revenue.

One more improvement could be tit-tit-tat-tat i.e. modifying the coefficient only if there are 2 consecutive flows that don’t meet the SLA. And, increasing the coefficient if there are 2 successful flows that meet the SLA.

Similarly, more experiments can be run with extending the learning phase to more observations in network behavior.

8. Learnings

8.1.Moving from VM to local installation of Ubuntu

As the size of the virtual topology kept increasing and the load on the network started increasing, VM was unable to handle all the load by itself. There were several instances where the CPU was completely occupied. Since in a VM the resources are shared with the host PC, there leaves a significant reduction in the amount of resources available for Mininet to keep the network occupied.

8.2.Moving the local SDN controller and database to the cloud

To ease up the resources even further, the SDN controller was tried to move to the cloud on Amazon Web Services (AWS) cloud. It was a simple transition. POX controller was cloned from github onto amazon Linux installation on AWS. Security measures taken to allow only hosts from only the local PC's IP address and the port for the POX controller that is 3366.

The database server was one bulky application that consumed a lot of processing power and memory. This was also moved to the cloud. Initially it was tried to move onto Amazon Relational Database Services (RDS), however there were issues connecting to Amazon RDS from java. This was mainly because Amazon RDS gives a single database even on Microsoft SQL Server. To overcome this issue, he database was moved to Microsoft Azure. Which allowed creating of multiples databased on a single server, just like on a physical device.

8.3.Moving back SDN controller to the local machine

It was observed that communicating with the SDN controller on the cloud introduced lot of delay in the network. So, the controller was moved back to the local machine on ubuntu alongside Mininet.

However, the database server continued to stay on the cloud, as the database interaction of the program was at the end of the program. And at times during the generation of a new flow.

8.4.Moving the installation from a computer running on i5 to i7 processor

Initial tests were run on a 4th gen i5 processor that had a 3MB cache memory. Which lead to a lot of packets being dropped. The processor couldn't process all the packets that were generated in the network.

8.5.Deciding on the conditions for changing in the value of the coefficient

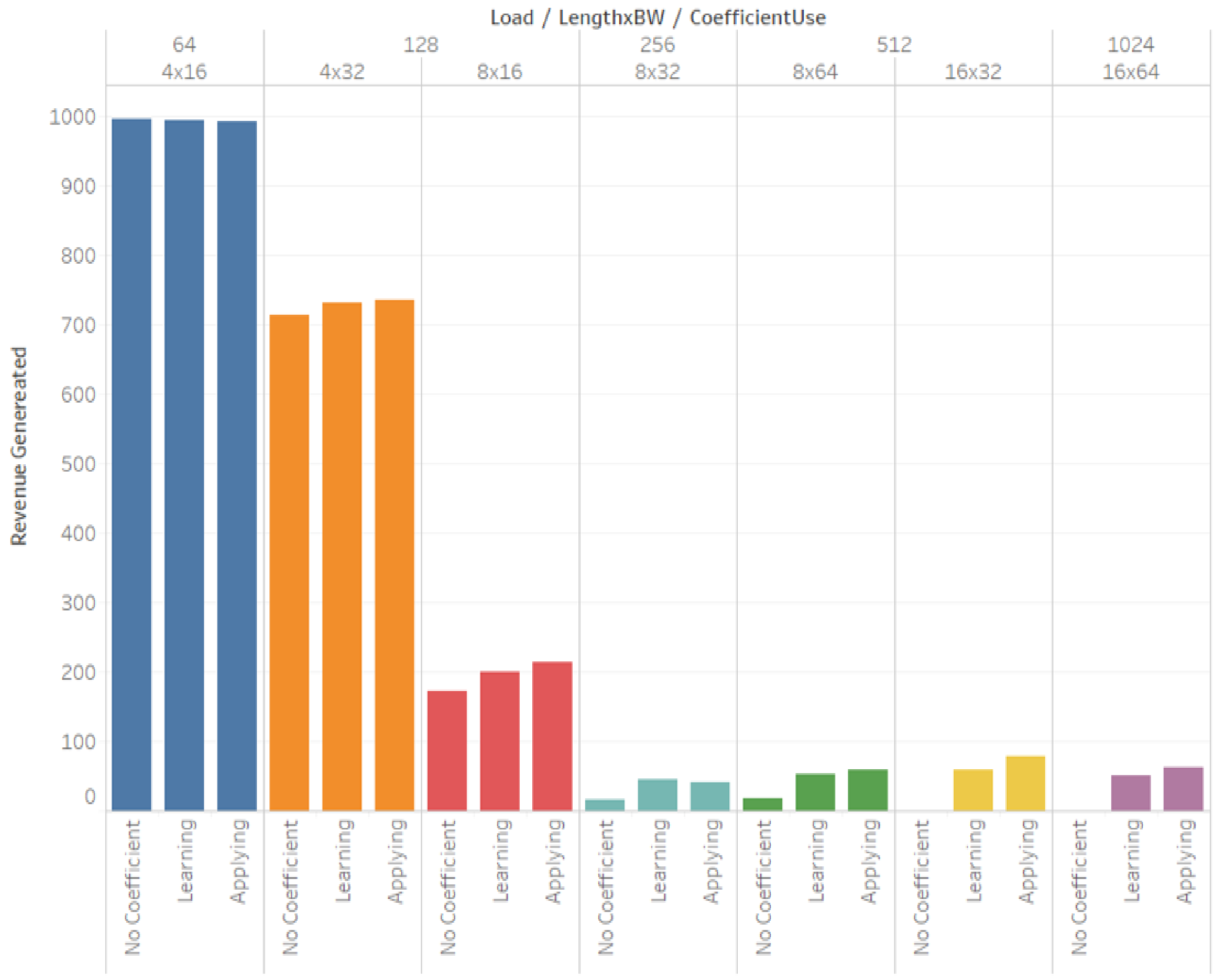
Tit for tat was applied to the value of the coefficient. In the learning phase, the coefficient was started with a value of 1. If a flow did not meet the SLA, the value of coefficient would be decreased by multiplying it with 0.9. If later a flow satisfied the SLA, the value of the coefficient would be multiplied by 1.1. This led to the value of the coefficient going down to 0 with heavy loads and no new flows being generated, which implied the value of the coefficient would never increase. So, a bottom limit of 0.1 was set and an upper limit was set to 1 for keeping a limit on the ever-increasing value of the coefficient for lower loads.

9. Summary

The virtual network topology has been set up in Mininet with 160 hosts on each side of the network, with 16 hosts connected to a switch. Totaling up to 320 hosts in the entire network. Flows are generated between a randomly chosen host from the first network to another randomly chosen host in the second network. Thus, making the all the packets flow through the link between the central routers and congesting that link.

Different sessions have been run with different values of duration and target bandwidth to test different load conditions on the network. Initially experiments were run with each simulation generating 100 flows each. It showed how machine learning helped identify congestion and help meet SLA for flows in the network and increase number of flows that generate revenue. To verify the results further, the experiments were run with 500 flows and later with 1000 flows in each simulation.

Once the session was run without any blocking coefficient, all the sessions were run again with tit for tat algorithm to learn an optimistic value of blocking coefficient. And this value was later used to apply the blocking coefficient on the network to maintain SLA and increase the number of flows generating revenue.



Applying tit for tat, the number of flows that meet the SLA, increased. This has been observed mostly with high loads which have higher changed of congestion and the network performance degrading. This is most prominently seen in the sessions with 16x64, where the revenue earned without applying the algorithm was 0, as there were no flows that met the SLA. After applying the algorithm to learn the coefficient, the number of flows that generate revenue was increased to 50.02 (100 %). And while applying this learned value of the coefficient to generate flows, the revenue increased further to 61.93 (100 %).

In extreme cases, the fewer the number of flows, the better of the performance. Like for example in the case of duration =1 second and bandwidth=256Mb/sec, 500 flows generate revenue. As the number of flows are increased, the performance degrades a lot. For example when the duration was made to 256 seconds (128 flows running simultaneously), the number of flows generating revenue reduced to 0.

Although the results show an improvement, with applying the coefficient, it might not be the best approach. Future work, focusing on getting a better value of blocking coefficient might prove to be better.

10. References

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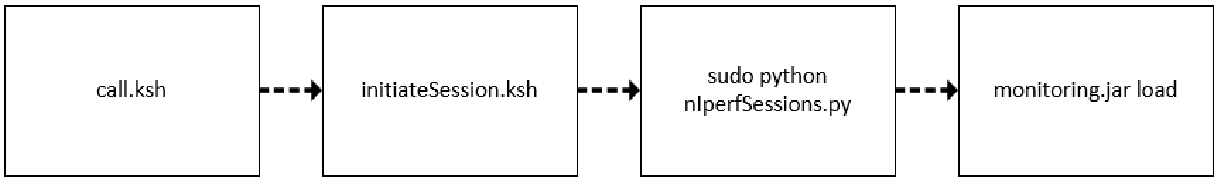
11. Appendix

11.1. Folder structure

File Type	File Name
Folder	archive
Python Script	Properties.py
Shell Script	call.ksh
Shell Script	initiateSession.ksh
Java Executable	monitoring.jar
Python Script	nIperfSessions.py
Shell Script	results.ksh
Text File	dbcon.properties

The package to create virtual SDN topology in Mininet, generate and collect data consists of several Python scripts, Shell scripts and a java executable file. The source codes for all the files can be found at https://github.com/nabarunjana/mininet-test

11.2. Initialization flow



11.3. File Description

11.3.1. archive

The archive folder consists of archived files generated in batches with specific parameters such as duration of each flow, the target bandwidth for each flow, the type of the flow: e.g. without any coefficient, learning the value of the coefficient, applying the coefficient, etc.

11.3.2. Properties.py

This python script is written to help ease the make changes to the database the program connects to. This is like the Properties class in java. This has methods for reading a file and getting a property. This is used in the program to read database connection properties specified in the dbcon.properties file.

11.3.3. call.ksh

This is a shell script that is the starting point for the program that can keep track of the batches that run with the required session parameters and load the details later to the database into a table called sessionmap. This calls initiateSession.ksh with the values of length of the flows, the target bandwidth and the phase of the experiment.

11.3.4. initiateSession.ksh

This shell script does some maintenance jobs such as zipping all the files generated and moving zipped files to the archive directory.

Once the folder cleared, it calls the nIperfSessions.py to create the virtual topology with the parameters from call.ksh and decides upon the number of flows to generate during the experiment and start generating flows and collecting data.

11.3.5. results.ksh

This shell script keeps a track of the pairs that were selected along with the bandwidth and amount of data that were transferred between them. The results for each host pair are appended to the results.txt file.

11.3.6. nIperfSessions.py

This is the main python script that creates the virtual topology after inheriting Mininet.Topo class, and adding switches, hosts, and links. Once the topology is set up, it starts the network and dumps all the configurations.

Once the topology is set up, it will set up monitoring the network performance ad host device statistics.

It then creates new threads for each flow, which in then selects 2 random hosts (one from each subnet) and performs IPerf and ping to measure bandwidth and delay between them. The output of these tests is put into individual files for each pair that is selected.

11.3.7. monitoring.jar

This is a java executable file that when called with the command line argument of load, loops through all the files in the current folder and checks for the desired generated files, parses them, and loads them into the database as a batch. At the end it inserts a row into the batch_run table that has a count of the number of rows that were inserted into each table.

To create the database schema automatically, the monitoring.jar application may be called with the create command line argument. This relies on the dbcon.properties for getting connection details. To load an archive file again, the monitoring.jar application may be called with the zip command line argument followed by an optional BATCH_ID.

To delete all entries related to one batch I'd, the monitoring.jar application may be called with the delete command line argument followed by the BATCH_ID.

11.3.8. dbcon.properties

This file has details for the program to connect to the database, with simple parameters such username, password, database etc. This is used by nIperfSessions.py and monitoring.jar.

e.g.

```
host=18.222.28.122
user=mydbuser
port=1433
password=passwd
database=mydb
dbserver=sqlserver
```

11.4. Setup

The whole program works in a Linux environment with Mininet, Python, Java, and SQL server.

The below commands are useful to install the necessary components in Ubuntu and to set up the environment with SNMP and necessary tools:

```
sudo apt-get update
sudo apt-get -y install git
cd ~
git clone git://github.com/mininet/mininet
mininet_installed=`./mininet/util/install.sh -a|tail`
echo $mininet_installed
sudo apt-get -qqy install curl gawk net-tools python-pip python-pyodbc openjdk-8-jre freetds-
bin freetds-dev
pip install numpy

sudo apt-get -qqy install snmp snmpd snmp-mibs-downloader
echo "Downloading MIBs"
echo `sudo download-mibs|wc -l`
mkdir -p ~/.snmp/mibs
sudo sed -i -re 's/([a-z]{2}\.)?#rocommunity/rocommunity/g' /etc/snmp/snmpd.conf
sudo service snmpd restart

#Clone mininet - test
codethere=`ls ~/mininet-test|wc -l`
if [ $codethere -le 0 ]; then
	git clone https://github.com/nabarunjana/mininet-test
	mkdir mininet-test/archive
	chmod 777 mininet-test/*sh  mininet-test/*py
fi
sudo curl https://packages.microsoft.com/keys/microsoft.asc | apt-key add -
sudo curl https://packages.microsoft.com/config/ubuntu/16.10/prod.list >
/etc/apt/sources.list.d/mssql-release.list

sudo apt-get update
sudo ACCEPT_EULA=Y apt-get -qqy --allow-unauthenticated install msodbcsql
# optional: for bcp and sqlcmd
sudo ACCEPT_EULA=Y apt-get -qqy --allow-unauthenticated install mssql-tools
echo 'export PATH="$PATH:/opt/mssql-tools/bin"' >> ~/.bash_profile
echo 'export PATH="$PATH:/opt/mssql-tools/bin"' >> ~/.bashrc
source ~/.bashrc
# optional: for unixODBC development headers
sudo apt-get -qqy install unixodbc-dev
sudo apt-get -qqy install xfce4 xrdp
echo xfce4-session >~/.xsession
sudo service xrdp restart
```

11.4.1. Known issues:

Sometimes, curl fails to add the mssql source to add to the source list and needs to be added by exclusively switching to the root user (sudo su) and then executing the command and then exit back to user mode. And then continue with the further steps of installing msodbcsql and mssql-tools.