Modelling TCP/IP Traffic of a Convergent Campus Wireless Network

Albert Espinal, Rebeca Estrada, Carlos Monsalve

***Abstract*—** With the deployment of new devices, protocols and applications, network traffic is changing to adapt to these trends. Therefore, it is necessary to analyze the impact over services and resources in data networks. Traffic classification of network is an important requirement to optimize traffic engineering and adequately provision quality of service. In this paper, we propose to analize the traffic in an university campus wireless network, throught the collected data by means of a novel sniffer that ensures the user data privacy. We focus in packet size. The results show that this traffic has a bimodal behaviuor with packets around 60 and 1300 bytes. It is also observed that IPv4 packets represents a big impact over IPv6, mainly TCP packets. And applications such as SSL and HTTP mark this trend. Numerical parameters for poisson distribution are presented in order to compare and simulate such traffic.

***Keywords*—** packet size, sniffer, traffic classification, traffic modeling.

I. Introduction

UNDERTANDING and analyzing the network traffic is an important requisite for planning the network security policies, provide quality of service to applications, and for optimizing the network resources such as bandwidth and delay.

Additionally, it is important to consider factors that influence over traffic, such as the deployment of IPv6 on the Internet, the massive use of applications, and new technologies and devices. The study from Cisco Systems: forecast and trends [1], predicts that by 2022, each person will generate a monthly traffic of 50 GB, compared to 16 GB in 2017. It is expected that the number of network devices will grow from about 18 billion in 2017 to about 28,5 billion in 2022. It is predicted that smart mobile traffic represents 44% compared to 18% in 2017. The traffic from wireless and mobile device will account 71 percent of total IP traffic. Regarding the applications, it is expected that the IP video represents 82% of the global traffic.

In packet-based networks, like the internet or the Wireless Local Area Networks (WLANs), the transmission of information is performed in discrete packets [2]. For analyze and modelling the network traffic, we can to considerate two variables: the packet size and the inter-arrival time [3]. This study is focus on packet size (or packet length). This variable has a stochastically behavior [4][5] which is monitored for the corresponding analysis.

In practice we can measure the traffic network by means of active polling and passive monitoring [6]. The active method generates new traffic, inject it into the network, while passive method consists on monitor, and capture the network traffic. One drawback of the passive method is the privacy of the data to be captured, because the traditional packet sniffers saves the entire packet: headers and payload [7]. We use a novel sniffer that process and save only the header for analysis. The passive measurement can be performed at various levels like byte, packet, flow, and session [8][9]. We centered this study at packet level because is independent of the protocols, and avoid the encrypted payload.

In this work, we proposed to analyze the traffic of a convergent campus wireless network, determine the contribution of protocols and applications, and estimate statistical models that represent and simulate these traffics.

The rest of the paper is organized as follows: section II provides information about related works; in section III we show the data collection, classified by type of traffic, by protocols, and by application, according to the variable packet size. Section IV presents the traffic model that characterize the realistic traffic analyzed. The paper ends with the conclusion in section V.

II. Related Works

Many works have analyzed the network traffic based on packet size, using methods such as statistical analysis, pattern recognition, length of the application messages, packet flows, user behavior, etc. Additionally, these studies had suggested models to simulate the realistic network traffic.

In [10], Zhang et al. presented a state of the art about traffic classification with emphasis in methods based on exact matching, machine learning, and heuristic methods. Around the year 2000, the internet traffic that was tri-modal with packet sizes around 40, 765 and 1.500 bytes [11]. In [12], Sinha et al. observed that the internet traffic was bimodal at packet sizes of 40 and 1500 bytes. Wu et al. in [13] analyzed flow records in an internet service provider and classified this by applications using machine learning. A study for

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identifying network traffic based on message size analysis is present in [14], and a Gaussian model is proposed for characterize the application-level protocols. Lee et al. in [15] present a study about the self-similarity of traffic using bandwidth frequency distribution. In [16] a work that classify network traffic using three classification approaches based on transport layer ports, host behavior and flow features is present. In [17] Zhang et al. evaluate the amount of UDP and TCP traffic, in terms of flows, packets and bytes. A work over internet data traffic generated in a university campus and a model for predict internet data traffic is present in [18]. Cao et al. in [19] demonstrate that the number of active connections has an effect on traffic characteristics. In [20], Bo et al. showed that the distributions of packet lengths follow certain specific patterns, which indicates that they are dependent on the application. In [21] and [22] develop statistical methodologies to analyze package lengths based on the characteristics of peer to peer applications, with the complexity involved in the use of random ports and the identification of messages with encrypted data.

Regarding the traffic modelling, Vicari present in [23] a model for internet traffic from the user perspective, using distribution functions applied to data. In [24], Maheshwari et al. design a Hidden Markov model for network traffic and validate it for different packet sizes. In [25], Lee et al. presents an analysis of the wireless traffic of a TCP / IP network based on marginal distributions for the packet length and the arrival time of the packets. Mueller in [26] specifies a traffic model based on object sizes at the application layer applied to wireless network. A Pareto model associated with the arrival time between packets, and a hybrid mathematical model for the packet length is presented in [27]. Dainotti et al. in [28] use machine learning to model the arrival time and the length of packages. A modeling of the packet length from normal distributions applied to bimodal traffic is presented in [29].

III. Data Collection and Analysis

One of the critical issues in the process of capturing network traffic is the use of the packet sniffer. This is owing to the fact that they normally capture the entire packet, which includes headers and payload. We propose to use a sniffer that guarantees the data privacy called TinySniff, implemented by Espinal et al. in [30]. TinySniff permit to capture the following fields in the header for further analysis: total length (IPv4) o payload length (IPv6), source address, destination address, protocol (IPv4) or next header (IPv6), source port, and destination port.

We implement a scenario for capture realistic traffic in a university campus wireless network shown in figure 1. This wireless network has around 300 access point managed by a wireless LAN controller. On average between 5.000 and 6.000 wireless devices are connecting daily, with an allocation of 300 MB of bandwidth to the internet. This include devices such as smartphones, tables, and laptops.

We install TinySniff on a desktop computer with Linux Ubuntu version 16.04 LTS. Its technical specifications are: AMD FX-8300 Eight-core processor, 24 GB of RAM, and two-network interface cards (NIC) Ethernet. One NIC is for PC management, and another for capture traffic. We connect the NIC for capture, in a gigabit port of access layer Cisco switch, and configure this port as analyzer monitor (SPAM) for reflect the interested VLAN wireless traffic.

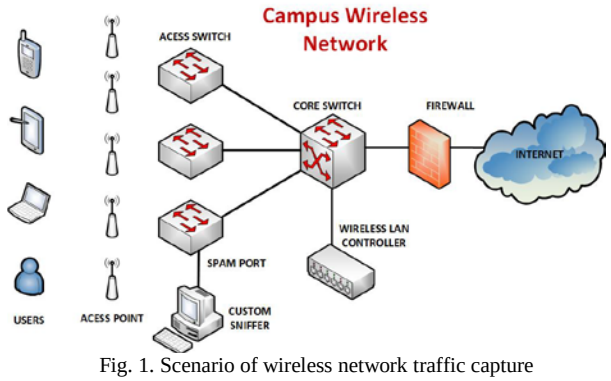

Fig. 1. Scenario of wireless network traffic capture

The traffic capture was collected on January 9, 2019 during 585 seconds between 15:18:48 and 15:28:03, peak traffic time. We collect near of 12 million of packets, with average 21.562 packets per second and average packet size of 742 bytes. Then, this data was classified by type of traffic (e.g. IPv4, IPv6 and ARP), by protocols (e.g. TCP and UDP), and by applications (e.g. SSL, HTTP, DNS, etc.). Table I, II and III present the traffic classification by type of traffic, by protocols, and by applications respectively.

From table I, it can be observed that IPv4 traffic is still more considerable than IPv6 in this network. Without ARP packets (these are local traffic), IPv4 represents 98.26% of the total traffic compared to 1.71% of IPv6. Table II shows that TCP traffic is significantly higher with respect to UDP (95.93% versus 4.02%). Regarding IPv6, ICMPv6 traffic is notable. Relating to applications, SSL (92.91%) and HTTP (6.25%) are the applications more relevant over TCP, while MDNS (41.63%) and SSDP (20.92%) over UDP.

Table 1. Data by Type OF Traffic

Traffic Type	Frequency	Percent
IPv4	11.527.297	96,30%
IPv6	204.189	1,71%
Others	238.940	2,00%
Total	11.970.426	100,00%

Table 2. Data by Protocol

Protocol	IPv4		IPv6	
	Frequency	Percent	Frequency	Percent
TCP	11.057.682	95,93%	0	0,00%
UDP	462.920	4,02%	121.022	59,27%
ICMP	6.695	0,06%	83.167	40,73%
Total	11.527.297	100,00%	204.189	100,00%

This work analyzes the variable packet size; this variable usually is between 40 and 1500 bytes. To analyze the packet size, we take intervals of 10 bytes for discrimination (i.e. 0-10, 11-20, 21-30, etc.). Figure 2 shows the behavior of packet size according to traffic type (IPv4, IPv6, ARP). Figure 3 and 4 present the variable packet size for IPv4 protocol and for IPv6

respectively. The analysis of IPv4 applications (under TCP and UDP) and packet size are shown in figures 5 and 6.

Table 3. Data by Application

	Protocol	IPv4		IPv6	
		Frequency	Percent	Frequency	Percent
TCP	SSL	10.273.141	92,91%	0	0,00%
	HTTP	691.052	6,25%	0	0,00%
	Others	93.489	0,85%	0	0,00%
	Total	11.057.682	100,00%	0	0,00%
UDP	MDNS	192.704	41,63%	98.118	81,07%
	SSDP	96.851	20,92%	4.425	3,66%
	DNS	56.321	12,17%	0	0,00%
	Others	117.044	25,28%	18.479	15,27%
	Total	462.920	100,00%	121.022	100,00%

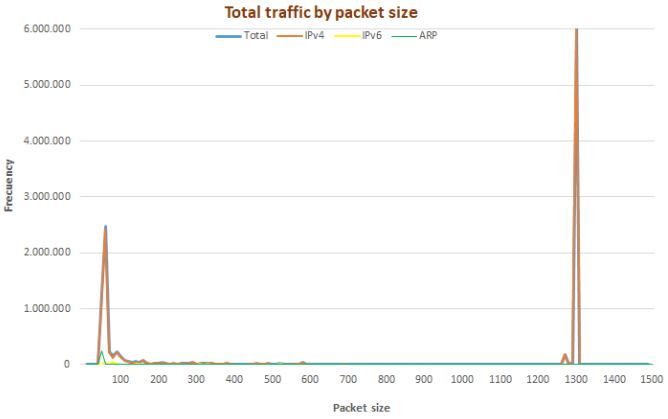

Fig. 2. Total traffic classified by length

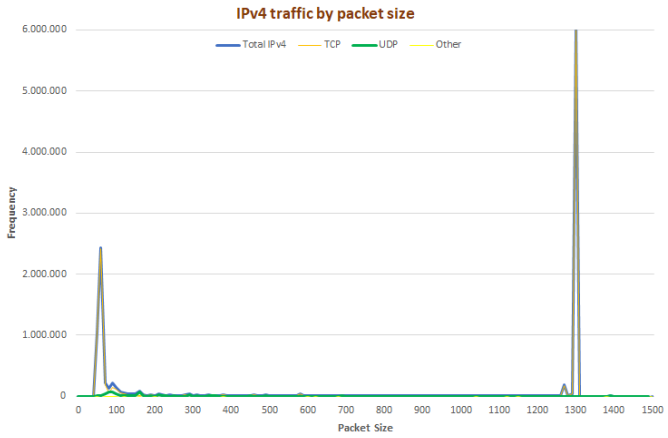

Fig. 3. IPv4 traffic classified by length

From Fig. 2, we can see that there is a bimodal traffic distribution with 48.32% of packets around of 60 bytes size, and 38,42% around 1300 bytes. For the first size, all traffic types contribute to this trend, while for second size only IPv4 traffic contributes. If we analyze the IPv4 traffic, it can observe that TCP is the main protocol over UDP and contributes over both bimodal trends.

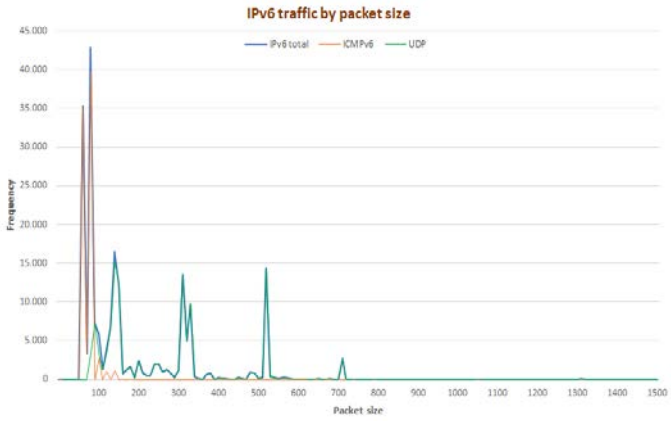

Fig. 4. IPv6 traffic classified by length

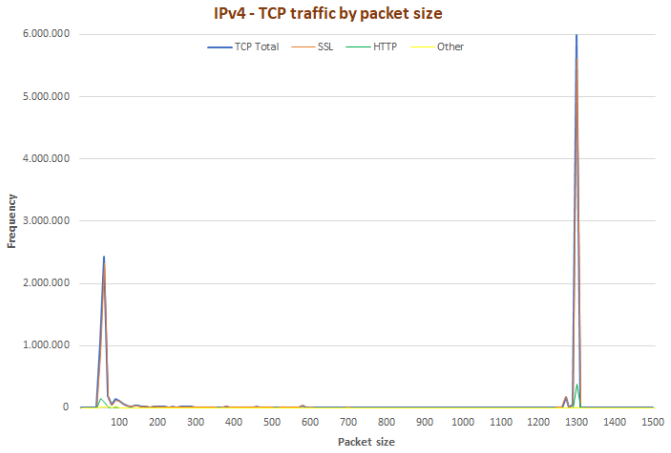

Fig. 5. IPv4 – TCP applications traffic classified by length

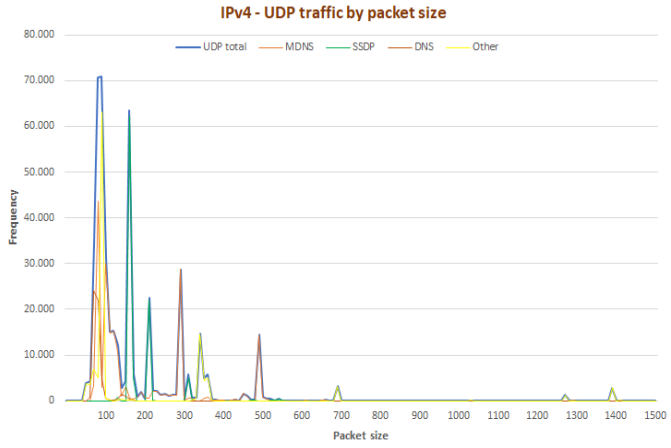

Fig. 6. IPv4 – UDP applications traffic classified by length

This IPv4 traffic is bimodal too, with 36.29% of packets around 60 bytes and 54% around 1300 bytes. TCP packets are the main factor in this behavior with 36.39% around 60 bytes and 56.31% around 1300 bytes. HTTP, SSL and TLS are the main applications and represent more than 99.16% of total IPv4 TCP packets and contributes with 35.17% of packet around 60 bytes and 56.23% around 1300 bytes. UDP packets contributes mainly around 100 bytes with 71.03%, and the

main application for this behavior is MDNS (around 80 bytes). Other UDP applications contribute with packets between 60 and 300 bytes in a sparse form.

The analysis of IPv6 traffic show that contribute with small packets around 80 bytes with 66.44%, mainly ICMPv6 packets. TCP and UDP traffic over IPv6 are still limited in this university campus wireless network. MDNS over UDP, is the most relevant.

IV. Traffic Modeling

Taking into account the analysis of the network traffic analyzed in the previous section, we estimate some models using the Poisson probability distribution function, based on traffic type, protocols and applications.

For total traffic presented in fig. 2, results a fitted model as a mixture of two Poisson distributions with parameters λ_1 = 93.22, and λ_2 = 1270.11. The probability that the length of a packet belongs to the first distribution is 0.448, while for the second distribution the probability of a packet following that distribution is 0.552. Finally, the model is the result of the sum of two Poisson distributions as in (1):

$$P(X = x) = 0.448 * \frac{e^{-93.22} 93.22^{x}}{x!} + 0.552 * \frac{e^{1270.11} 1270.11^{x}}{x!} \quad (1)$$

Where x is the ocurrence of packet size variable. In fig. 7 we show the simulate model for network traffic total.

For IPv4 network traffic the parameters are λ_1 = 93.42 and λ_2 = 1267.86. The probability that the length of a packet belongs to the first distribution is 0.409, while for the second distribution the probability of a packet following that distribution is 0.591. The model is showed in (2). For IPv6 network traffic, the model is as in (3), with parameters λ_1 = 396.88, and λ_2 = 105.99. The probability that the length of a packet belongs to the first distribution is 0.301, while for the second distribution the probability of a packet following that distribution is 0.699. Figures 8 and 9 show these simulate models.

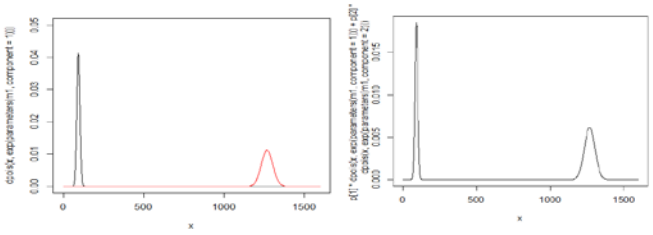

Fig. 7. Poisson model for Traffic Total

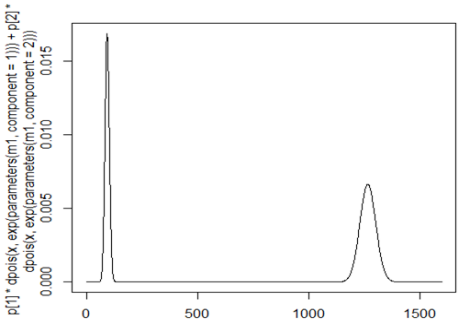

Fig. 8. Poisson model for IPv4 Traffic

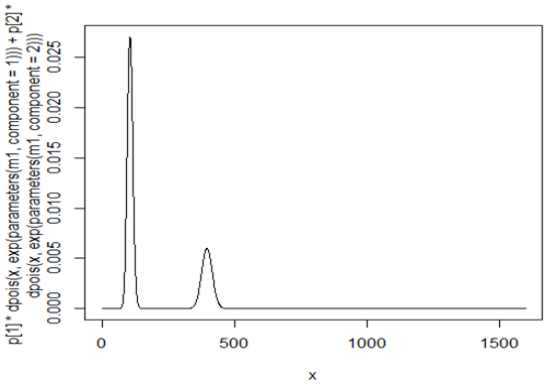

Fig. 9. Poisson model for IPv6 Traffic

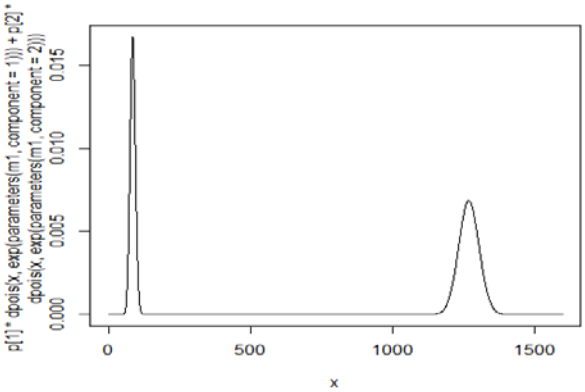

Fig. 10. Poisson models for IPv4 - TCP Traffic

Additionally, we present models for protocols TCP and UDP, over IPv4 and IPv6. Table IV resume the parameters of the models, where λ_1 represent average occurrence in interval 1, λ_2 represent average occurrence in interval 2, P_1 is the probability for a packet following the first distribution, and P_2 is the probability of a packet following the second distribution. For IPv6 only UDP Poisson distribution is necessary for fit the data. Fig 10 show the simulation of these models; and the equations in (4) (5) (6).

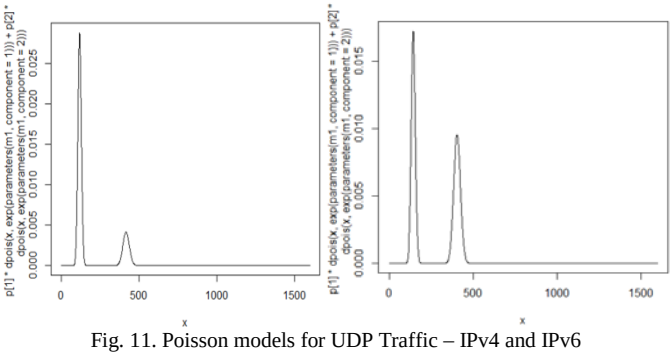

Fig. 11. Poisson models for UDP Traffic – IPv4 and IPv6

Table 4. Poisson Model Parameters for IPv4 / IPv6

Protocol		λ_1	λ_2	P_1	P_2
IPv4	TCP	1270.48	85.67	0.612	0.388
	UDP	418.09	119.06	0.212	0.788
IPv6	TCP	-	-	-	-
	UDP	405.15	143.58	0.482	0.518

$$P(X = x) = 0.409 * \frac{e^{-93.42} 93.42^{x}}{x!} + 0.591 * \frac{e^{1267.86} 1267.86^{x}}{x!} \quad (2)$$

$$P(X = x) = 0.301 * \frac{e^{-396.88}396.88^{x}}{x!} + 0.699 * \frac{e^{105.99}105.99^{x}}{x!} \quad (3)$$

$$P(X = x) = 0.612 * \frac{e^{-1270.48}1270.48^{x}}{x!} + 0.388 * \frac{e^{85.67}85.67^{x}}{x!} \quad (4)$$

$$P(X = x) = 0.212 * \frac{e^{-418.09}418.09^{x}}{x!} + 0.788 * \frac{e^{119.06}119.06^{x}}{x!} \quad (5)$$

$$P(X = x) = 0.482 * \frac{e^{-405.15}405.15^{x}}{x!} + 0.518 * \frac{e^{143.58}143.58^{x}}{x!} \quad (6)$$

Finally, table V presents the parameters for the applications that mainly contribute to the total network traffic. As describe, the mainly traffic are SSL and HTTP with 99.15% over TCP, and it´s 95.93% over IPv4, that represents 98.26% of total traffic in this campus wireless network. Fig 12 shows the pattern of SSL packets.

Table 5. Poisson Model Parameters for Applications

Protocol			λ_1	λ_2	P_1	P_2
IPv4	TCP	HTTP	1296.14	85.50	0.685	0.315
		SSL	1267.80	83.61	0.607	0.393
	UDP	DNS	81.94	177.39	0.935	0.065
		MDNS	107.33	353.83	0.670	0.330
		SSDP	362.64	178.61	0.067	0.933
IPv6	UDP	MDNS	405.15	143.58	0.482	0.518
		SSDP	398.54	214.47	0.420	0.580

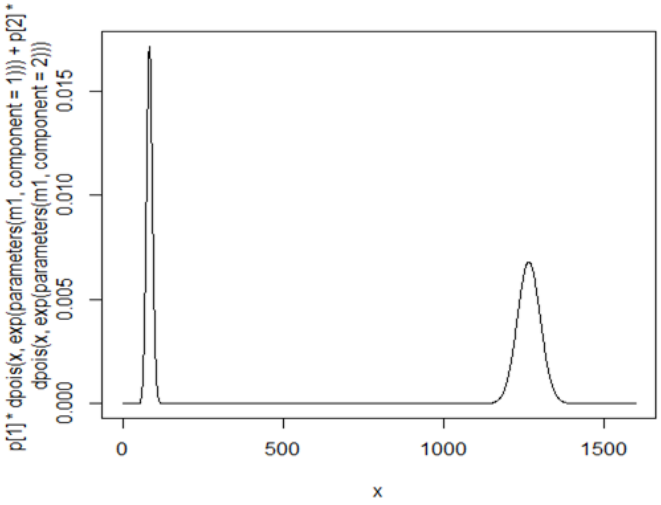

Fig. 12. Poisson models for SSL Traffic – IPv4

V. Conclusions

This paper presents results for stochastic behavior of packet size variable using network traffic measurements in a university campus wireless network. The results show that there is a bimodal traffic distribution with packets around 60 and 1.300 bytes. IPv4 packets represents a big impact in this behavior, mainly TCP packets, and the applications that mark this trend are SSL and HTTP.

Network administrators can use these results to design better networks and optimize network traffic in order to give security policies, QoS provisioning, and ensure efficient utilization of resources.

We development models for characterize the network traffic based using mixture Poisson distribution and provide the best statistical fit to the packet size variable of the dataset considered in this paper. These models simulate the data by traffic type, protocols and applications. Research community can use these distribution parameters presented for built traffic models and apply in other studies in the areas of computer networking and traffic engineering.

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