CABLE-TEC EXPO'15
OCTOBER 13-16 NEW ORLEANS

Society of Cable Telecommunications Engineers

Characterization and Impact of User Behavior of OTT Services.

Cablevisión Argentina shows a statistical analysis of its network

A Technical Paper prepared for the Society of Cable Telecommunications Engineers
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Abstract

Over the last few years the characterization of Over the Top services plays an important role in the area of capacity management. Cable operators are forced to invest in the network infrastructure as much as OTTs traffic demands. Furthermore, network operators have no benefits for carry these services. Even if some content operators negotiate for paid access to connect with cable operators, as Netflix with Comcast.

Modeling the Internet growth is important both to understand the current network and to project its future.

Cablevisión is the largest MSO in Argentina and one of the biggest of Latin America, with 2 million broadband subscribers in five geographic areas, with services whose speeds range from 1 Mbps to 50 Mbps. The objective of this paper is to analyze, over all the company cable modems some statistic parameters and metrics for few OTT services, particularly Netflix. And from these parameters understand OTT service user behavior, how they impact on the network and their tendency.

The findings can be used by any provider applying the simple tools they have available, which also allows them to define their own methodology. As a consequence, not only can they perform a more accurate capacity management but also evaluate the trend for bandwidth growth.

Content

1. Introduction

In this work we present the characterization of the cable modem network traffic generated by two of the most relevant streaming applications: Netflix and YouTube. Understanding their characteristics is of major importance to evaluate their impact on cable networks.

Since the beginning of the telephone networks, operators have sought to characterize and to dimension traffic. Fr. Johannsen wrote two early papers providing approximate solutions to outcomes in telephone exchanges [1,2]. With the characterization of traffic in the late 50's between a terminal and a host, Leonard Kleinrock based the mathematical foundations for packet switched networks [3,4].

When the Internet began to grow exponentially, over 20 years ago, the works related to traffic characterization began to multiply. As an example, with some previous experience suggesting that the Poisson or Markov models were unsuitable for Internet traffic, Leland proposed a model of self-similar traffic in his foundational work carried out since 1989 [5]. Later, Paxson, Crovella and Claffy have continued working in the same subject [6,7,8].

More oriented to specific applications, there have been multiple works about characterization of Web servers' traffic and their behavior [9,10,11], broadband user behavior [12,13] and live streaming system workloads on the internet [14,15,16].

Related to Netflix, J. Martin from Clemson Univ. and T. Shaw from CableLabs, carried out an investigation, in 2011-2012, that in one network scenario, they observed that a backlogged TCP flow achieved a throughput of 6 Mbps while a Netflix session consumed less than 3 Mbps of bandwidth [17].

In addition, regular reports from Cisco [18], Akamai [19], and Sandvine [20] based on different methodologies show how access speed and traffic volume evolve. Particularly, Sandvine reports, by analyzing its hundreds of customers, the characterization of OTT traffic and its impact on the network during the peak period [21]. Cablevisión's observations are similar to USA data with Netflix usage accounting for 35% of traffic, being the leader application in the peak period, and expect to grow 4-fold to 2019.

2. Internet Attitudes and User Preferences

For the last three years we have been carrying out a study about several application traffic and we have found that OTT video services represent more than 50% of Cablevisión total downstream traffic. It should be noted that the supply of these services in Argentina is not as extensive as in other parts of the world. Most popular video streaming services are Netflix and YouTube but, since last year, Netflix is the service with more downstream traffic and more consumption among our customers, being the top usage application particularly during the peak period[1]. However, the percentage of subscribers using Streaming Media applications is not the highest, other services such as Web Browsing or Bittorrent are still taking the lead. Figure 1 presents the percentage of concurrent subscribers versus total traffic volume of the top usage applications. As we can see, Streaming Media does not reach 5% of concurrent subscribers but its consumption is the highest. It is noteworthy that just the 5% of total concurrent subscribers consume the half of total downstream traffic.

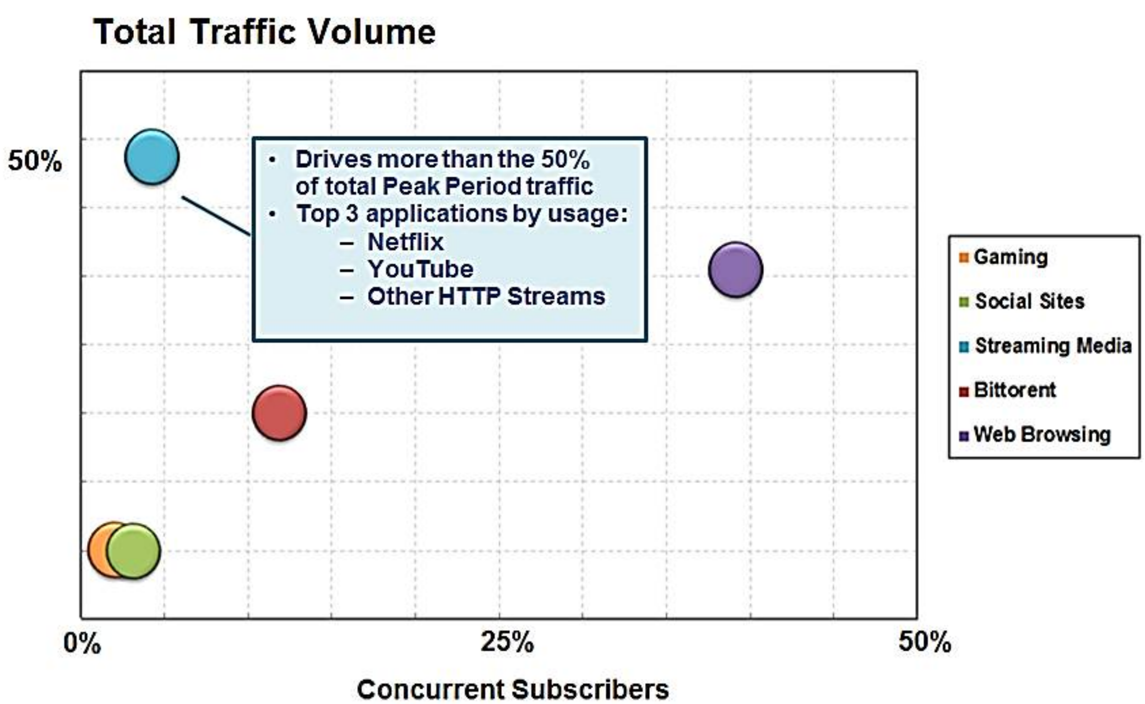

Figure 1 – Top 5 Peak Period Applications.

A detail of Netflix and YouTube downstream traffic and their concurrent subscribers is showed in Figure 2. We can observe that Netflix represents the 35% of total downstream traffic and YouTube the 15%, and the percentage of concurrent subscribers is about 1.5% and 2%, respectively.

[1] Peak period: 8 p.m. – 10 p.m.

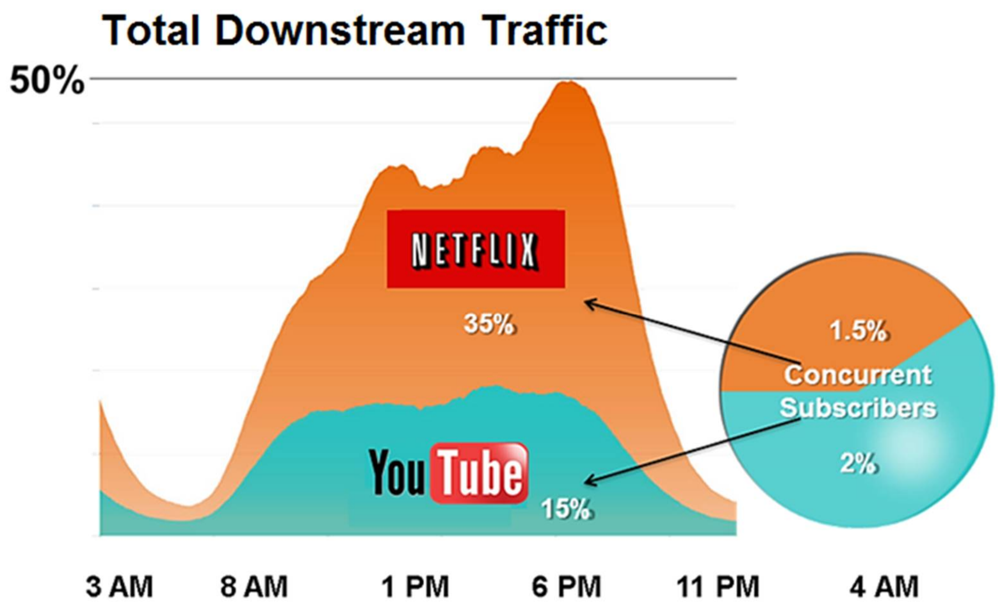

Figure 2 – Netflix and YouTube downstream traffic and their concurrent subscribers.

Comparing with the rest of the world, according to Sandvine's report [21] about the USA's fixed access networks, Real-Time Entertainment maintains as the dominant traffic category in the region. This category includes Netflix, which is the leader during peak period traffic, being responsible of the 36.5% of downstream traffic. YouTube is the second ranked application, which accounts for 15.5%.

Regarding Latin America, Real-Time Entertainment is also the leading source of traffic. However in this region, YouTube is the dominant traffic category, accounting for the 33% of downstream traffic while Netflix is responsible for 6.6%, occupying a position within the top 10 but well below other services. However, compared with previous Sandvine's reports, this service has tripled in just 18 months and it is noted that Netflix is the leader in paid-streaming video market in Latin America.

Sandvine's reports examine a representative cross-section of the world's leading fixed Communications Service Providers, however Cablevisión data is not part of these reports. Therefore, Cablevisión is not included in Latin America's fixed access networks study.

It is remarkable the similarity between the USA and Cablevisión regarding to the percentage that Netflix and YouTube traffic represent of the total traffic and the difference with other Latin America's CSPs. This is due to the fact that Netflix is one of the top usage applications accounting for 35% of the total traffic of Cablevisión, almost the same percentage as in the USA. In contrast, for a representative cross-section of Latin America fixed's CSPs, YouTube is the application accounting this percentage, as it can be seen in Figure 3.

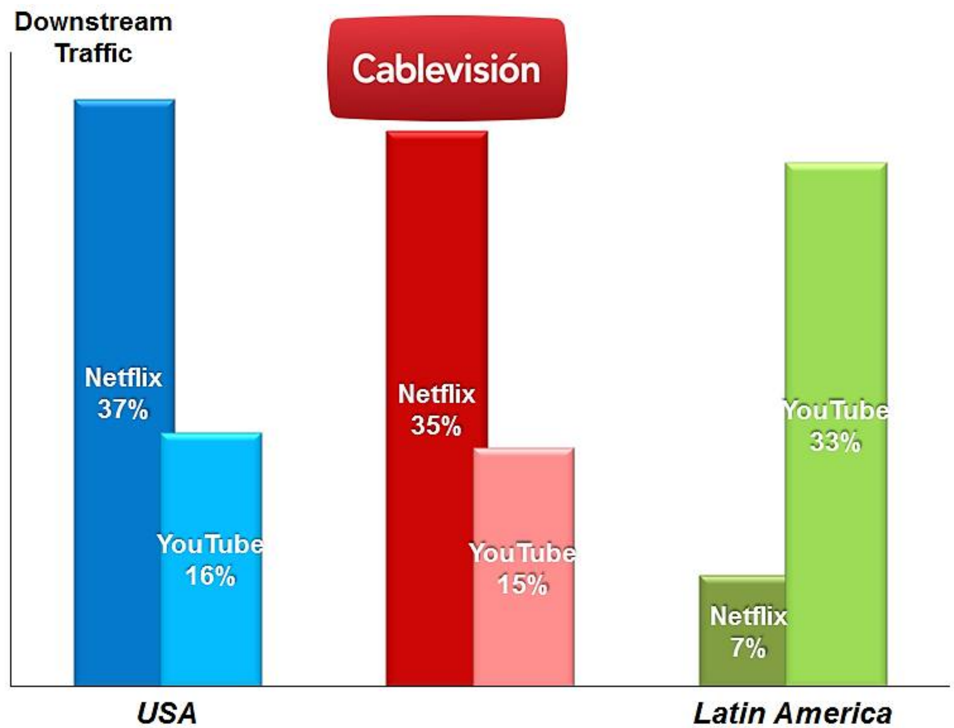

Figure 3 – Netflix and YouTube traffic proportion against other regions.

3. Access Speed and Netflix User Behavior

For the last year, we have been analyzing, various monthly statistical measures and parameters for Netflix service, including the average bandwidth for residential subscribers (98% of our subscribers) and the traffic volume they consume according to their access speed.

There is evidence that the relation between the number of subscribers and the traffic volume fits sub-exponential distributions [22]. Such distributions are *long tailed* and can describe in a convenient way the high variability. Historically, some long tailed distributions have an origin in income distribution, for example, Pareto and Log-Normal. The latter is one of the least understood functions and with greater applications [23].

3.1. Log-Normal Distribution

A random variable X is said to be Log-Normally distributed if $log(X)$ has a Normal distribution (Figure 4). The probability density function of a Log-Normal distribution is:

$$f_X(x;\mu,\sigma) = \frac{1}{x\sigma\sqrt{2\pi}} e^{\frac{-(\log x-\mu)^2}{2\sigma^2}}, \quad x > 0$$

Where μ is the mean or expected value of *log(X)*, and it is a measure of central tendency. And σ is the standard deviation of *log(X)*, which is also called shape parameter.

The other important statistical measure is the median or 50th percentile. It is the number separating the higher half of a population from the lower half. It can be used as a measure of location when a distribution is skewed, as is Log-Normal distribution. Basically, because when the distribution is the Normal, the population usually reports the mean. However, when the distribution is skewed, population tends to report the median, as the median is less affected by outliers.

A property of the Log-Normal distribution is that the mean is higher than the median and the median is higher than the mode, unlike the Normal distribution where all these values are equal.

There is evidence that the traffic volume fits a Log-Normal distribution, in fact Cablevisión's total consumption fits it. Therefore, mean and median are significant values to analyze in order to characterize Netflix user behavior, since they are the most representative parameters of this service's consumption.

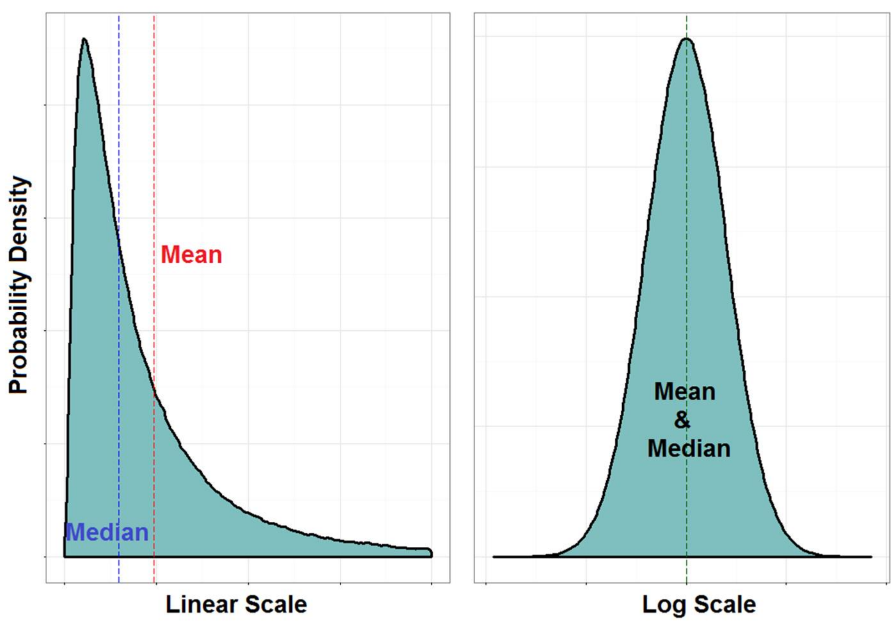

Figure 4 – Log-Normal probability density represented by linear and log scales.

3.2. Impact of User Access Speed on Netflix Consumption

To determine the possible relation between consumption, average bandwidth traffic, and access speed, we partition the Netflix users in five groups according to their access speeds: 1 Mbps (corresponding to 1% of total subscribers), 3 Mbps (corresponding to 31% of total subscribers), 6 Mbps (corresponding to 46% of total subscribers), 12 Mbps (corresponding to 18% of total subscribers) and 30 Mbps (corresponding to 1% of total subscribers). It is worth remarking that there is no difference in the results between Ethernet cable modems and cable modems with a Wi-Fi Access Point incorporated. So, we can consider that the Netflix users are homogeneous among these two groups for each access speed.

Taking account these classes, Figure 5 presents the Netflix service monthly penetration, its mean usage and its median traffic volume, that is, the consumption value that exceeds the 50% of each group's population.

For Netflix consumption distribution, the total usage mean is the consumption value that exceeds the 30% of the total population and is about 32GBytes, almost the same mean value of users with 6 Mbps of access speed. That's because, they represent the mean population.

The same happens with the median of total consumption that is about 15 GBytes (45% of the mean consumption) and it's also the same median value of users with 6 Mbps of access speed.

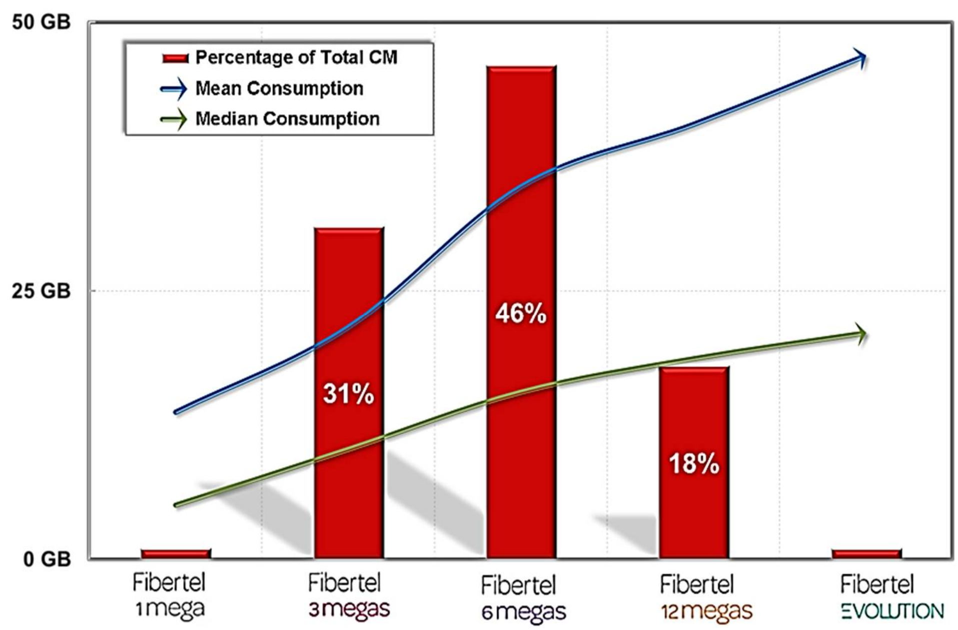

Figure 5 – Netflix's monthly consumption statistics among access speeds.

Then, given the access speed, the increase in these two parameters is significant, particularly between 1 Mbps and 3 Mbps and between 3 Mbps and 6 Mbps. One reason for this increase is the type of content and the associated consumption which can be accessed with the different speeds.

Netflix reports [24]:

- 0.5 Mbps: Required broadband connection speed
- 1.5 Mbps: Recommended broadband connection speed
- 3.0 Mbps: Recommended for SD quality
- 5.0 Mbps: Recommended for HD quality
- 7.0 Mbps: Recommended for Super HD quality
- 25 Mbps: Recommended for Ultra HD 4K quality

3.3. Impact of User Access Speed on Average Bandwidth Netflix Traffic

We also carried out a bandwidth per user analysis depending on the access speed, as shown on Figure 6. It can be seen that, regardless of users' access speed, the bandwidth per customer reaches a peak of about 4 Mbps. That is because of the available content and the required broadband to access them. Taking a look at the chart, we found three different kinds of behavior. It can be seen that the average bandwidth traffic of subscribers with 1 Mbps and 3 Mbps of access speed tends to be constant throughout the day, except for a few traffic peaks occurring away the peak period. But in turn, a significant difference exists between both series due to the limitation of the bandwidth of users with lower access speed. However, although the other users (6, 12 and 30 Mbps) have different access speeds, their average bandwidth traffic is similar each other and less constant. At first glance, there doesn't seem to be major differences in Netflix service performance between these three groups, except during the busy period when users with 30 Mbps of access speed show certain advantages over the others. Again, it is assumed that the similarities are due to the quality of the content available, the required broadband to access them and user preferences.

Table 1 shows the average broadband traffic per user by access speed during the peak period. Differences and similarities mentioned above can be seen through this parameter: for users with 3 Mbps it's 111% higher than users with 1 Mbps and for users with 6 Mbps it's 58% higher than users with 3 Mbps. While for subscribers with 6, 12 and 30 Mbps the gap is of 10% and 3%, respectively.

In conclusion, there are no significant differences among the average bandwidth traffic of subscribers with 6 Mbps, 12 Mbps and 30 Mbps. On the contrary, providing higher access speed to the subscribers cause an increase in the mean and median consumption.

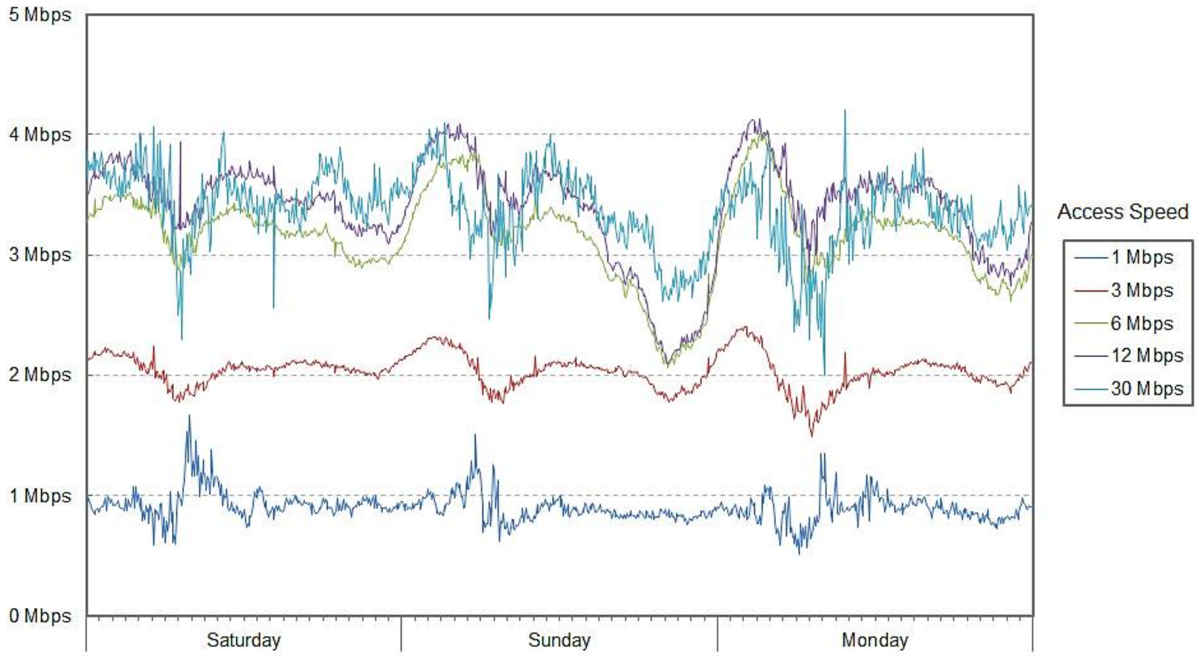

Figure 6 – Average bandwidth Netflix traffic's comparison between access speeds.

Access Speed	Avg Bandwidth Traffic (Mbps)
1 Mbps	0.9
3 Mbps	1.9
6 Mbps	3
12 Mbps	3.3
30 Mbps	3.4

Table 1 – Average bandwidth Netflix traffic per access speed during the peak period.

4. Netflix Open Connect CDN: Improving the QoE

In this section we present some statistical results of the impact on traffic which involves the addition of the Netflix Open Connect Content Delivery Network [25] in our backbone.

In Argentina, broadband users access streaming video content, most of which are located in the USA. Thus, the impact of Round Trip Time in services performance is very important. From our service groups a typical RTT is in the order of 120-150 msec. In contrast, in the USA, it's significantly lower. It is for this reason, that CDN usage turns crucial. In our country, improving reference locality is more essential than Internet Exchange Points development. Very different case is that of Brazil where most of the content being accessed is regional and there has been a strong IXP development. How the CDN OpenConnect operates is out of scope of this paper, and we refer the reader to [26].

To make a local cache of Netflix content, two server farms were installed in two different data centers of the company. Each of them consisted of 3 servers with 12 Gbps capacity called Open Connect Appliance, which were provided by Netflix. Since we were receiving about 100 Gbps of peak daily Netflix traffic, we had to connect with Netflix, in Brazil, via international peering to provide the traffic demand that the CDN can't deliver because of its capacity limit.

When connecting to Brazil instead of the USA, increased throughput is obtained since it is inversely proportional to the RTT, which is smaller at a shorter distance. This is possible because Netflix uses DASH protocol which in turn runs over TCP [27].

Moreover, accessing to contents that are closer will generate a significant increase in bandwidth consumption, as long as the condition of the access network allows it. This could create problems of saturation in sites where there were no previous problems and increase the expected consumption in downstream ports where more carriers will be added. In an already congested downstream port, major drawbacks to the existing will not be generated, because the bitrate of the contents will be adapted to the subscribers' bandwidth.

4.1. Measuring Performance Before and After the CDN

At the beginning of the Netflix Open Connect CDN implementation, since it only applied to half of the service groups, we performed various tests based on comparing the Netflix traffic before and after this implementation for the two groups: Using and Not Using the CDN. It should be noted that service groups not using the CDN provided the Netflix traffic through Internexa link with Brazil.

In Figure 7 we show two time series about average bandwidth Netflix traffic per user from service groups using or not using the CDN. It can be seen that the increase in performance is noticeable for service groups using CDN, even more during the morning when workload is low. We have found that the traffic generated by Netflix users using CDN doubles the traffic generated by those not using CDN. However, during the peak period, the gap between both series lowers to 23%, as we can see in Table 2.

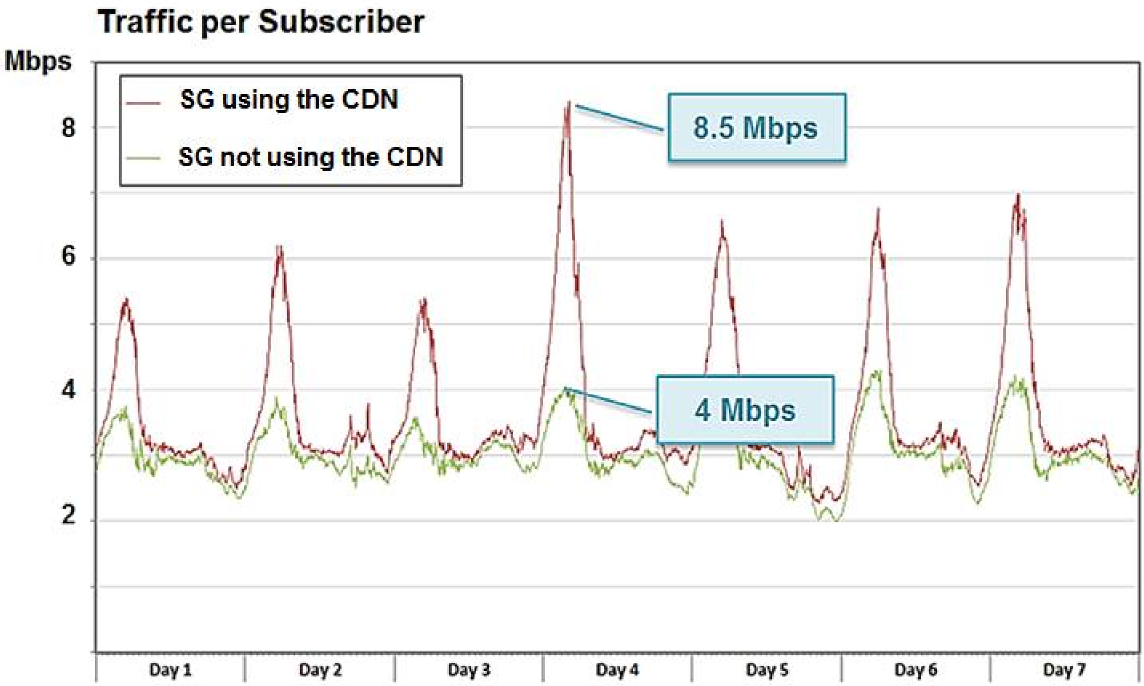

Figure 7 – Netflix traffic per subscriber from Service Groupsusing or not the CDN.

	Using CDN	Not Using CDN	Gap
24 hours	8.5 Mbps	4 Mbps	53%
From 3 p.m. to 12 a.m.	4.7 Mbps	3.6 Mbps	23%
Saturday, from 3 p.m. to 12 a.m.	3.2 Mbps	2.7 Mbps	15%
Saturday, from 8 p.m. to 10 p.m.	2.7 Mbps	2.5 Mbps	7%

Table 2– Netflix traffic statistics from Service Groups using or not the CDN.

4.2. Projecting Total Bandwidth Traffic Growth per Service Group

Based on the above results we can estimate the total bandwidth traffic growth in the service groups. If we assume that the increase in traffic, since the implementation of the CDN, has been 23% and has maintained the same amount of active flows, the associated downstream Netflix traffic should grow at exactly the same proportion. Let:

- *N: "Previous Netflix Traffic"*
- *T: "Previous Total Traffic""*
- *N': "Post Netflix Traffic"*
- *T': "Post Total Traffic"*
- Δ: *"Traffic Growth"*

So,

$$N' = N + \Delta N \ , \quad T' = T + \Delta T \text{ and } \quad \Delta T = \Delta N \quad \rightarrow \quad T' = T + \Delta N$$

$$\frac{T'}{T} = 1 + \frac{\Delta N}{T} \rightarrow \frac{T'}{T} = 1 + \frac{\Delta N}{N} * \frac{N}{T}$$

Thus, the percentage increase in total traffic will be the product between the percentage increase in Netflix traffic and the percentage that Netflix represents of total traffic. Assuming that in a service group not using the CDN the relation N/T is 35% and the percentage increase is 23%, we get:

$$\frac{T'}{T} = 1 + 0.23 * 0.35 = \mathbf{1.0805}$$

So, the total traffic growth of the service group will be 8.05%, supposing that the number of concurrent subscribers remains invariant.

5. Significant Growth in Netflix Users

With the objective to analyze the evolution of Netflix users among Cablevisión subscribers, we have been carrying out a monthly study of the current penetration of this application. We have discovered a significant growth during the first six months after the CDN implementation and then, this growth started to slow down. Appreciating the value of this information for capacity planning, we began to develop a time series model to forecast Netflix users, the amount of traffic they will be sharing and, as a consequence, the impact on the access network. Time series provides powerful statistical models that are commonly used in business and economics where data frequently occur in the form of time series [28]. This section includes a brief description of this methodology.

5.1. Netflix Usage Consumption

In order to understand the evolution of Netflix users, we have created two groups of subscribers: we define "Loyal Users" as those who consume Netflix's contents every month from the beginning of this study and "New Users" as those who consume Netflix content for the first time.

Almost by definition, loyal users will consume Netflix service again and again over time. Then, it's important to know if the number is growing and what the user's tendency is, in order to perform capacity planning according to this growth.

In our observations, carried out monthly, we have found that loyal users represent 22%, new users account for 12%, while the rest of them ("Other Users") consume Netflix contents from time to time (Figure 8). We have noticed that the number of loyal and new users began to slow down during the last months.

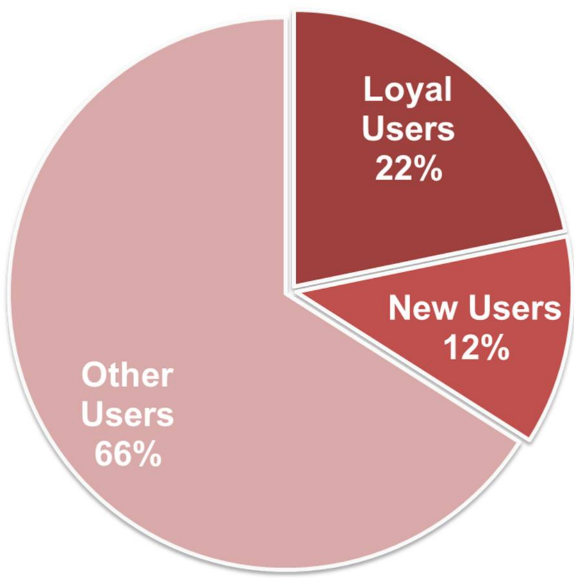

Figure 8 – Distribution of Netflix users among our subscribers.

5.2. Time Series and ARIMA Model

Time series is an ordered sequence consisting of successive values of a variable over equally spaced time intervals. A stochastic model for a time series will generally reflect the fact that observations close together in time will be more closely related than observations further apart.

The usage of time series models allows us to:

- Obtain an understanding of the underlying characteristics and structure that produced the observed data, through different analyzing methods.

- Fit a model and proceed to forecast future values based on previously observed values, monitoring or even feedback and feedforward control.

Models for time series data can have many forms and represent different stochastic processes. When modeling variations in the level of a process, three broad classes are: the autoregressive (AR) models, the integrated (I) models, and the moving average (MA) models. These three classes depend linearly on previous data points. Combinations of these ideas produce autoregressive integrated moving average (ARIMA) models.

Non-seasonal ARIMA models are generally denoted as $ARIMA\ (p,d,q)$ where p is the order of the autoregressive model, $d$is the degree of differencing and q is the order of the moving average model.

5.3. Forecasting Our Growth

As we mentioned above, after the implementation of the Netflix Open Connect CDN we began to carry out an analysis of Netflix users' growth. At first, we observed that the percentage of monthly increase was about 20%. However, this growth began to decline over time, and monthly increase reduced to 2%, as we can observe in Figure 9.

By fitting this data through statistical software, we observed that ARIMA was the best-fitting model. Then, to forecast future Netflix users, we have selected a confidence interval (CI) of 95%, a CI gives an estimated range of values which is likely to include an unknown population parameter, the estimated range being calculated from a given set of sample data.

Figure 9 also shows the predicted values that are represented with the red line and the limits of the CI are represented with two grey dotted lines. The wide of the CI will be thinner when the amount of previous data increases and, as a consequence, forecasted values will be more precise. By the moment, with only ten previous values (09/2014 to 06/2015), the estimated growth is about 10% to December 2015.

It's noteworthy that this model has been applied successfully to forecast the whole population of Cablevision subscribers by fitting properly the three parameters of the ARIMA model. Now, we are working on fitting the same three parameters for Netflix users while we continue collecting data to develop the model.

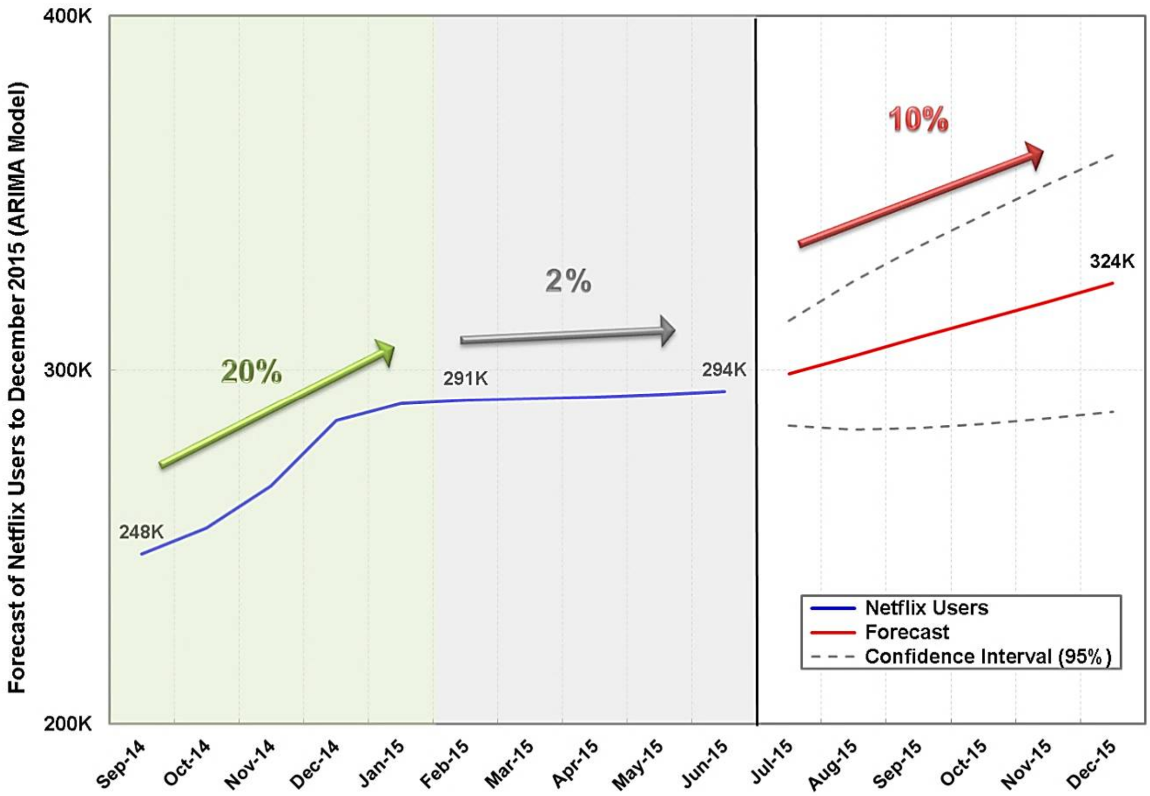

Figure 9 – Monthly evolution and forecast of Netflix users among our subscribers.

Conclusion

The characterization of OTT services' user behavior, the OTT traffic impact on the network and their tendency became essential for capacity planning. This paper presents different analysis of Cablevisión network and the findings can be used by any provider, applying simple tools to evaluate their trends.

By analyzing some statistic parameters over the current network, we observed that OTT service traffic represents more than 50% of the total downstream traffic, being Netflix and YouTube as the two top usage applications; but, they aren't the most popular. However, it's remarkable that only 5% of total concurrent subscribers consume the half of total downstream traffic.

Since Netflix's consumption can be fitted to a Log-Normal distribution, values such as mean and median become significant to analyze, since they are the most representative parameters of this distribution. Then, we found that increased access speed leads to higher mean and median consumption, particularly between the lowest access speeds. However, we observed that this conclusion is not true regarding to bandwidth traffic. In fact, the average bandwidth Netflix traffic per user, whose access speeds are 6 Mbps, 12 Mbps and 30 Mbps, is almost the same.

After the implementation of the Netflix Open Connect CDN we found an improvement in our subscribers' QoE; during the peak period, service groups using the CDN experienced an increase of 23% of Netflix traffic. Based on this result, we present a combination of equations to estimate the total bandwidth traffic growth in a service group.

For the purposes of estimating Netflix user growth, we proposed a time series model not only to understand the characteristics of this tendency but also to forecast the amount of traffic the users will be sharing and, as a consequence, the future impact on the access network.

Netflix is a key driver in Cablevisión traffic growth and due to this, we are carrying out a study of a new model of traffic engineering, taking account the impact of OTT services studied in this paper.

Abbreviations

ARIMA	autoregressive integrated moving average
CDN	content delivery network
CI	confidence interval
CSP	communications service providers
DASH	dynamic adaptive streaming over HTTP
IXP	internet exchange point
MSO	multiple system operator
OTT	over the top
QoE	quality of experience
RTT	round trip time
SG	service group
TCP	transmission control protocol

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