A New Model for VoIP Traffic Generation

Carlos Ignácio de Mattos*, Eduardo Parente Ribeiro* and Carlos Marcelo Pedroso*
*Federal University of Paraná
Graduate Programm on Electrical Engineering
Centro Politécnico, Curitiba, Paraná, Brazil
Email: {mattos, edu, pedroso}@eletrica.ufpr.br

***Abstract*—In this work a new model for VoIP traffic generation is proposed. The innovation of this model consists in modeling the user behavior instead of the aggregated traffic. We have analyzed the call holding time and the time interval between calls to characterize the user behavior. In order to provide an accurate packet generation, the data nature was modeled by identifying the time for packet transmission and the time interval between packets. Those variables of the proposed model were characterized with probability distributions. The parameters of the distributions were obtained with the analysis of real data collected from two major Brazilian telecommunications carriers. A VoIP traffic simulator was implemented and its results were compared with real data to validate the model. The similarity between synthetic and real data indicates that our model works properly and can be used for VoIP networks modeling and workload generation.**

***Index Terms*—Traffic Models, Voice over IP, Voice Codecs.**

I. Introduction

The appropriate design of telecommunications networks is essential for an efficient utilization of the available resources. If the allocated bandwidth for an application was not the ideal there could be an over or under estimation of the resources. Great attention must be given to the service nature for networks planning: while a Web application demands bandwidth, low round trip time and low packet loss, real time applications require, in addition of these features, low delay and jitter.

According to Banks et al. [1] a model is defined as a representation of a system for the purpose of studying it. In order to allocate the resources in an accurate way and evaluate the application performance, it is necessary to use accurate traffic models. The goal of network modeling is to represent the traffic behavior as faithful as possible to reality. This enables one to preview the impact of changing network characteristics in the service quality. In this way it is possible to evaluate the Quality of Service (QoS) and correctly allocate the resources for a given application. Daniel and Virgilio [2] stated that a good model needs to represent the reality with simplicity and accuracy for make it easier to understand and provide reliable results.

Traditional commuted telephonic systems were extensively studied and have well known models that use the exponential distributions for call holding times and intervals between sessions [3]. The use of the exponential distribution to model call holding time is directly related to user behavior. The commuted telephonic service is tariffed by time. This fact usually induces the user to make short telephone calls and, as a consequence, long calls are rare. Gradually, the telephonic services are migrating to Voice over Internet Protocol (VoIP). Many VoIP services are not tariffed by time but by a fixed fare, usually monthly, regarding the bandwidth provided. The change in the billing method has the potential to modify user behavior and long time telephonic calls may not be a rare event anymore. By consequence, the traditional models fail to model VoIP traffic accurately.

In this work we present a new model for VoIP traffic. The novelty of our proposal is to model the user behavior instead of the aggregated traffic, leading to many benefits such as greater simplicity and accuracy if compared with existent approaches. The proposed model was parametrized with real data collected from two major Brazilian telecommunications carriers. The first one offers a pure VoIP service that means that the user receives and originates calls using VoIP. The second company offers a mobile phone service and converts the traffic internally to VoIP in order to achieve easier and less expensive transport. The accuracy of the proposed model is confirmed through a computer simulation by the comparison of the model workload generation with real data.

The article is structured as follows. Section II describes related works, including traditional and recent publications for VoIP modeling. Section III describes the proposed model. Section IV shows the parameters adjusted to the model that were obtained from real traffic analysis. Section V describes the implementation of a simulator to traffic generation and presents an analysis of the obtained results. Finally, conclusions and future works are presented in section VI.

II. Related Works

In the early 90´s, Leland et al. [4] showed that the nature of LAN Ethernet traffic is statistically self-similar. A process is self-similar when it keeps part of its characteristics along a certain range of scales. This result has contrasted former works that stated the data traffic was markovian [5] and it stimulated additional research, as [6] and [7].

Several works apply the self-similarity concept in modeling VoIP traffic, [8], [9] and [10]. However, the data used in these works were obtained from enterprises or universities with a limited traffic generation for its particular case. Chen et al. [11] studied a VoIP mobile phone traffic from a commercial telephonic carrier and observed a long tail behavior in the call holding time. Pedroso et al. performed in [12] an analysis of the user session behavior of the VoIP traffic in a major Brazilian carrier and the results suggest that the call holding times can be well described by a heavy tail distribution, leading to a self similar traffic.

In [13] packet traces from different voice codecs were analyzed and their output was modeled with a stochastic process. They analyzed Constant Bit Rate (CBR) codecs, codecs with silence detection and Variable Bit Rate (VBR) codecs. The proposed model for the CBR codec, G.711 and G.729, is very intuitive. By the fact that they had analyzed the codec output directly, with no queue and time processing effects, CBR model is just a table that contains features of packet generation, like time between packets, the packet size, and control information. They used an ON-OFF process in order to model the codecs with silence detection, G.723.1 and iLBc. Speech time is modeled by ON state and silence time by OFF state. The recognition of the ON or OFF phases is not a trivial task since there are break intervals during the speech time may be recognized as silence interval. To identify the ON-OFF phases they applied heuristic methods. These methods have observation windows that is used to identify the silence and speech intervals. The authors had to face two problems with this method: (a) avoid to misunderstand silence intervals with break intervals and (b) do not ignore a significant part of speech phase. GSM AMR and iSAC VBR codecs modeling was made under perfect network conditions. GSM AMR has a Voice Activity Detection (VAD), differently from G.723.1 or iLBC. It sends empty packets for synchronization and silence descriptor packets for background noise when there is silence. This noise creates a comfort sense for the VoIP user. Therefore, GSM AMR packet stream do not completely stops in the silence period and it is difficult to apply the ON-OFF model as suggested by [13]. iSAC sends packets with size varying from 21 bytes to 166 bytes. This behavior is a VBR traffic, however the silence and talk phase are still acknowledged. The authors used a memory Markov Chain (MMC) [14] to model the VBR codec traffic. They tested different MMC parameters until a good performance is achieved. For the iSAC codec, better results were obtained removing control traffic.

Our work made an analysis of VoIP traffic by decomposing the aggregated traffic according the individual user behavior. The resulting model will be used to implement a synthetic VoIP traffic generator. Our model is simpler than [13] because it uses probability distributions to model the performance metrics instead of detecting voice activity by windowing process or other heuristics methods. Also our paper complements a previous work [12] with a deeper analysis.

III. Model Description

The general idea of the proposed model for VoIP traffic characterization is based on the Scalable URL Reference Generator (SURGE) model [15], originally designed for Web servers modeling. SURGE model is different from others because it was developed based on the user behavior and the nature of the data. In VoIP scenario, we propose four variables that can be seen in figure 1:

(i) Time Interval Between Calls (TIBC): Represents the time interval between successive calls.
(ii) Call Holding Time (CHT): Describes the user call holding time.
(iii) Time for Packet Transmission (TPT): It is the time spent to the packet transmission.
(iv) Time Interval Between Packets (TIBP): It is the time interval between successive packets for an user session.

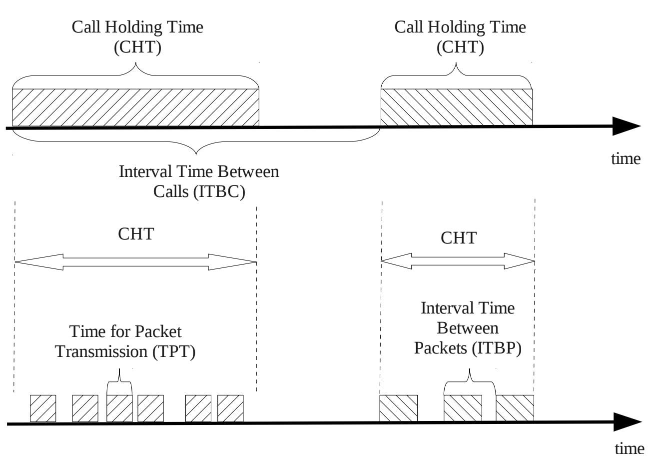

Fig. 1. Packet Traffic of Two Different Calls with the Identification of the Parameters that will be Estimated

The variables of the model will be characterized by probability distributions. The call holding time and the time interval between calls are variables at the session level. When the session is active, packet generation starts according to the other two variables: time for packet transmission and time interval between packets. These variables represent the data nature and they are strongly related to the codec in use. We analyzed packet traces from telecommunications carriers to determine probability distributions that fit well with the empirical data and to find their parameters.

A. Data Set

Data were collected from two telecommunications carriers. Carrier 1 offers a pure VoIP service and Carrier 2 offers a mobile phone service but internally converts the traffic to VoIP. On both carriers, data collection were carried out at the network backbone, which consists in a non congested Ethernet network in both cases. Packets belonging to the same session were identified based on the IP address (source and destination) and the sequence number from RTP protocol. The latter is necessary because the same user could have different destinations calls simultaneously, in a conference for example. In the following sections a detailed description of the data collection for each carrier is presented.

1) Carrier 1: The VoIP service offered by Carrier 1 uses SIP protocol (Session Initiation Protocol) [16] for signaling and RTP protocol (Real Time Protocol) [17] for data transport. The SIP protocol was designed to interact with other Internet protocols, initializing, modifying and ending sessions, independently of the media or application. When session begins, voice is coded/decoded by a codec and transmitted with RTP protocol. The codecs in use are ITU G.711 [18] and ITU G.729 [19]. G.729 is used by 93% of the sessions and the remaining sessions use G.711. G.711 has a sampling frequency of 8 kHz and 8 bits per sample resulting in a rate of 64 kbps. This codec guarantees a high quality for the coded voice and it is used frequently as a reference standard. G.729 codec tries to achieve a good voice quality with lower transmission rate. G.729 possible rates vary among 6.4 kbps, 8 kbps and 11.8 kbps, depending of the desired voice quality. Both codecs in use at this carrier are CBR (Constant Bit Rate).

The analyzed network had about 10000 users by the time of the data collection, in September 2007. In general terms, the access network is formed by ADSL (Asymmetric Digital Subscriber Line) links. The VoIP traffic generated by users is transported by a non congested Gigabit Ethernet network. In order to collect the data, Ethernet switch ports, that serves as backbone, were mirrored in a way that the total VoIP system traffic was captured using the open source protocol analyzer Wireshark [20]. Call holding time was calculated with the analysis of the time interval between INVITE and BYE messages. These are SIP messages that indicate the beginning and ending of a session. The time interval between calls consists in the time between two consecutive INVITE messages. Note that only the sessions ended in a graceful way, with a BYE message, were analyzed. The time for packet transmission and the time interval between packets were obtained with the RTP packets analysis.

2) Carrier 2: Carrier 2 is a major mobile phone carrier that uses VoIP to transport the calls originated in the mobile phones destined to other carriers. The traffic is transfered from one carrier to another via an interconnection gateway. The voice coding is made by AMR (Adaptive Multi-Rate) codec [21] and the resulted data are sent through media gateways with RTP protocol. The signaling is made by BICC (Bearer Independent Call Control) protocol [22]. BICC messages IAM (Initial Address Message) and RLC (Release Complete Message) are used to identify the beginning and ending of a VoIP call. Time interval between calls was identified as the time between two IAM messages and the call holding time as the time between IAM and RLC messages. Carrier 2 has 80% of its clients with prepaid charging plans and remaining clients have postpaid plans. Data were obtained in two collections of eight hours done in weekdays in April 2009. The transport network is also a non congested Gigabit Ethernet.

IV. Model Variables Characterization

In this section, the probability distributions that characterizes each variable of the model and the good of fit tests results are shown. The methods used to verify the goodness of fit were Quantile-Quantile Plot (QQ-Plot) and Kolmogorov-Smirnov (KS) test. The QQ-Plot consists in plotting a distribution against another. When points gather on the 45° line it means a good adherence between both distributions. All statistic analysis in this work were made in the R statistic software [23].

A. Call Holding Time (CHT)

1) Carrier 1: It was observed a heavy tail behavior which can be modeled by Pareto type 2 probability density function. Pareto distribution is a heavy tail distribution that foresees extreme events [6]. Pareto type 2 or Lomax distribution [24] was used because traditional Pareto distribution does not represent the reality by the fact that it does not generate values lower than scale parameter. Pareto type 2 can generate values lower than scale parameter keeping a heavy tail behavior, like traditional Pareto distribution. Equation 1 defines the Pareto type 2 cumulative distribution function.

$$F(x) = 1 - (1 + \frac{x}{\beta})^{-\alpha} \tag{1}$$

Figure 2 illustrates the QQ-Plot results which confirms the adherence of empirical to theoretical data. Pareto shape and scale parameters, α and β, were obtained with the use of the maximum likelihood method. The obtained results are 2.16 for α and 63.43 for β. For values of $\alpha \leqslant 1$, the mean is not convergent and for $1 < \alpha \leqslant 2$, the mean converges but the variance does not [6]. The α value obtained is near the variance non convergence region, leading to a significant variability of the data. The average time of CHT was 143.7 seconds, while the standard deviation was 490.4 seconds for 10.210 sessions. For this reason, we applied the QQ-Plot to verify the adherence between empirical and theoretical distributions. Results are presented in figure 2. They indicate that Pareto type 2 distribution can characterize CHT properly.

2) Carrier 2: The analysis procedure in Carrier 2 data was similar to the previous carrier and the empirical data also showed a good adherence to Pareto type 2 distribution. Figure 3 presents graphically the adherence between the theoretical and empirical distributions using the QQ-Plot. The estimated values for the distribution parameters were: $\alpha = 3.12$ e $\beta = 39.17$. This α value indicates that the variability of the Carrier 2 CHT is lower than Carrier 1. In figure 3, because of a greater α value, less points appear in the tail of the distribution.

B. Time Interval Between Calls (TIBC)

1) Carrier 1: Time interval between calls in telephony is usually described by an exponential distribution [3]. Kolmogorov-Smirnov test was done with the empirical data and the theoretical exponential distribution. The obtained p value was 0.84. For the adherence hypothesis rejection p value must be less than 0.05 [25]. Therefore, this result confirms the classical results. The exponential distribution is parametrized only by the TIBC average which it was 1.125 seconds. As illustrated in figure 1, TIBC represents the time between two calls arrivals that was identified by the time interval between SIP INVITE messages.

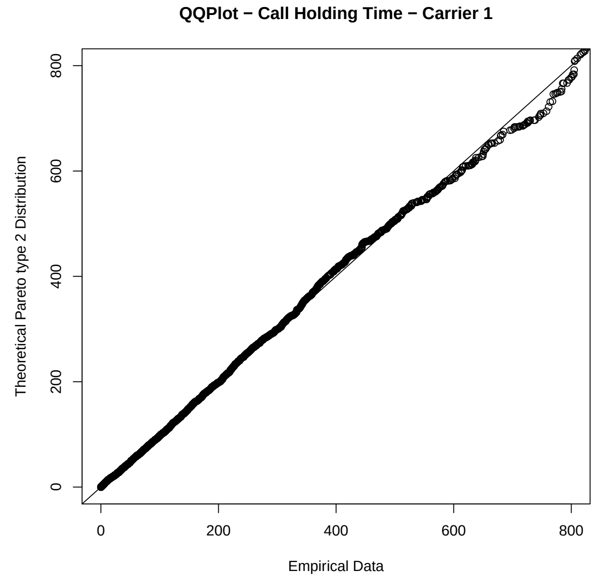

Fig. 2. Quantile-Quantile Plot of Random Pareto type 2 versus Measured CHT Values at Carrier 1

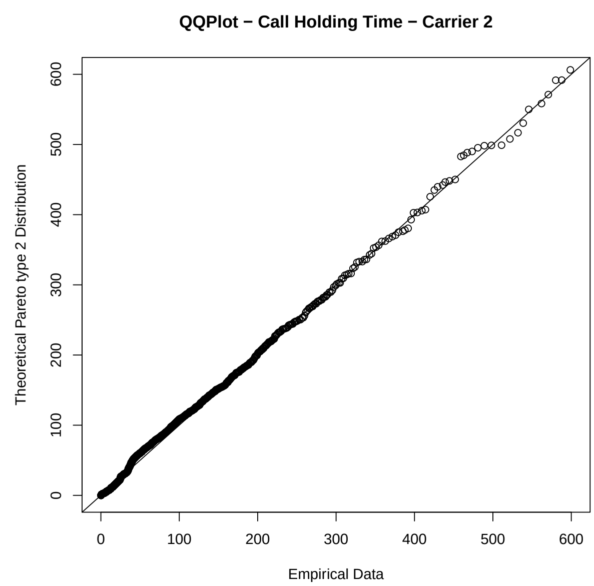

Fig. 3. Quantile-Quantile Plot of Random Pareto type 2 versus Measured CHT Values at Carrier 2

2) Carrier 2: The Carrier 2 data have also adhered to the exponential distribution, as expected. The Kolmogorov-Smirnov test resulted in a p value of 0.83 which confirms mathematically the good adherence. The TIBC observed was 0.506 seconds.

We also observed a fast decay of the auto-correlation function (ACF) for TIBC series confirming the independence of successive call arrivals, leading to a Poisson Process.

C. Time for Packet Transmission (TPT)

In order to characterize TPT it is necessary to identify the packet sizes and its occurrence frequency. It was observed that the packets sizes tends to remain constant for the entire session. Packet size is determined by the payload (coded voice) and the Ethernet, IP, UDP and RTP headers. The payload varies along the sessions but the headers have a fixed size of 70 bytes [26].

1) Carrier 1: Sessions initiated with G.711 codec have two typical packet sizes, 284 and 364 bytes. When a session starts, the codec chooses the packet size and this will remain until the end of the session. The number of initiated sessions with packet size of 284 bytes was almost the same of sessions with packet size of 364 bytes. The time for packet transmission is the packet size and link transmission rate ratio. The network bit rate is 1 Gbps resulting in TPT of 2.27μs and 2.91μs.

G.729 codec generates packets with sizes of 134, 144 and 154 bytes. Of the total number of sessions initiated with G.729, 3.77% were with 134 bytes, 71.70% with 144 bytes and 24.53% with 154 bytes. TPT time for each packet size are: 1.07μs, 1.15μs and 1.23μs.

2) Carrier 2: Carrier 2 uses AMR codec for voice coding. This codec generates packets with sizes of 137 bytes, 163 bytes and 172 bytes whose proportion in the sessions were 3%, 75% and 22% respectively. The used link rate has 1Gbps, thus the times for packet transmission are: 1.10μs, 1.30μs and 1.38μs.

D. Time Interval Between Packets (TIBP)

The codecs in use in both carriers are CBR. However, our model was designed to be applied to variable bit rate (VBR) codecs. As we collected the traffic at the network backbone, even the packets of CBR traffic sources show some variable delay caused by queue and machine processing, motivating the use of the proposed model. Additionally, the capacity of studding the impacts of the machine processing delay is an advantage of our model. In the following items the characterization of the TIBP is described.

1) Carrier 1: As the traffic sources are CBR, TIBP remains almost constant along the sessions but presents some variation. In order to model TIBP, we identified the TIBP average and used probability distributions to model the variation around the mean. For G.711 codec, TIBP averages are 20ms and 30ms for the packets of 284 bytes and 364 bytes respectively. For the G.729 codec the mean time intervals are 10ms, 20ms and 30ms for the packets of 134 bytes, 144 bytes and 154 bytes, in that order.

The analysis of the variation around the mean revealed different behaviors for the regions above and below the mean time. Those variations were modeled in a separate way. For the G.711 codec, it was observed one pattern for the mean time of 20ms and three patterns for the 30ms mean time. The G.729 codec traffic has produced five patterns whose mean interval is 20ms, two patterns for the 10ms interval and five patterns for 30ms interval. In [27], there is a table that shows all the identified variation patterns, the probability distributions and its parameters.

2) Carrier 2: Time interval between packets with RTP information was analyzed to determine TIBP. It was modeled with Pareto type 2 distribution with $\alpha = 3.85$ and $\beta = 37$.

V. Synthetic VoIP Traffic Generation

A. Simulator Description

In order to test the quality of the proposed model, we implemented a discrete event system simulator for workload generation. The simulator was implemented in Java language to make it independent of the platform. The proposed model in section IV consists in finding the probability distributions that adheres to the data and the distributions parameters. Thus, it was necessary to implement in the simulator a random variable generator (RNG) according to the required probability distributions. Pareto type 2 and Exponential distributions were generated using Monte Carlo method and Gamma RNG was implemented using the acceptance-rejection method [1]. The Gaussian RNG was implemented with the Box-Müller method [28].

In the simulator it is possible to configure all the variables of the model and also the link bandwidth. The operating principle is as follows. The clients start in inactive condition and pass to CHT condition according with the exponential distribution. The time permanence in the CHT is described by Pareto type 2 distribution. While the client is active, the session generates packets according to TPT and TIBP models described previously. The simulator was parametrized according to Carrier 1 data in order to test the modeling result of a pure VoIP traffic.

B. Simulation Results Analysis

In order to evaluate the quality of the proposed model, the simulated traffic was compared with real data. For this comparison, aggregated traffic at scale of 100ms from two hours of traffic in the busiest network hour was considered. It is known that the time series representing aggregated traffic presents a slow decay of its auto-correlation function for self-similar traffic. In a previous work [12], it was showed that aggregated traffic of Carrier 1 presents long range dependence which can be seen in the slow decay of the auto-correlation function. Figure 4 shows the ACF for real and synthetic data. Note that both the curves are quite similar and exhibit a long range dependence.

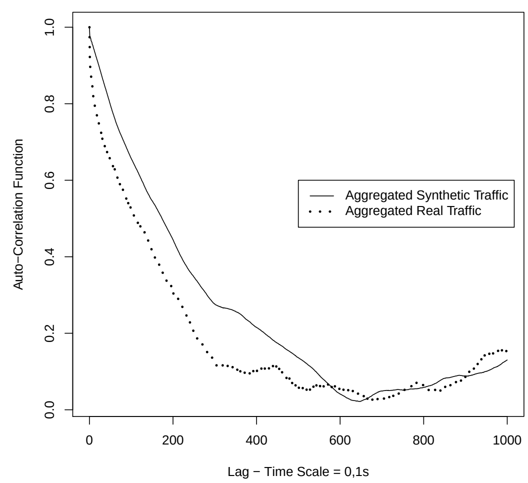

Fig. 4. Auto Correlation of the Aggregated Traffic. Long range dependence can be observed for both curves indicating that synthetic traffic has similar feature of real traffic.

Another way to evaluate the presence of the long range dependence is through the Hurst parameter (H). For self-similar series with long range dependence, $1/2 < H < 1$. The closer to 1 is the Hurst parameter, higher is the degree of the self-similarity and long range dependence [6]. Hurst parameter was estimated by the Wavelet method. Real traffic aggregated at scale of 10ms presented a Hurst parameter of 0.626 and the aggregated synthetic traffic had H = 0.663 at the same scale. This result denotes that both traffics present self-similar characteristics with long range dependence. The similarity of the curves in figure 4 and the Hurst parameter analysis indicates that synthetic data presents similar characteristics of real traffic and the proposed model properly characterizes the VoIP traffic.

VI. Conclusion and Future Work

We observed that the VoIP user has a different behavior than traditional telephony user, specifically in the call holding time. Long time calls are not rare anymore and traditional models fails to predict VoIP traffic. We proposed a new model for VoIP traffic that characterizes the user behavior using probability distributions. This approach is simpler than existing models for VoIP. We have identified the probability distributions and its parameters for the variables of our model through the analysis of the real data from two major Brazilian carriers. Call holding time was described by Pareto type 2 distribution. Carrier 1 present Pareto shape parameter smaller than Carrier 2. This result indicates that the VoIP user tends to make long calls more frequently than mobile phone user, as it was stated before. The time interval between calls has adhered to the exponential distribution as former works reported. We have modeled individual session behavior by characterizing the time interval between packets and the time for packet transmission. These two variables strongly depends of the codec in use.

We have implemented a simulator in order to verify model accuracy. The simulator was configured with Carrier 1 traffic parameters and synthetic data was generated for comparison with the real data. This comparison indicates that the proposed model mimics the real data traffic features, including its long range dependence characteristics. Our model can be used for VoIP traffic studies, as workload generation or network planning, among other applications.

As future work, we intend to model the more common VoIP codecs, especially VBR codecs. Instead of collecting data from telecommunications carriers, we intend to generate the packet traces using the international voice database [29] that it is used for codec development. We expect this approach will lead to data free from delays from network and machine processing, and the resulting model should characterize the codec behavior, allowing further research in performance of VoIP systems . At this time, we are also working in an application for capacity planing, including an estimation for MOS (Mean Opinion Score) perceived by the users, using the proposed model and computer simulation.

References

[1] J. Banks, J. S. C. II, B. L. Nelson, and D. M. Nicol, *Discrete-Event System Simulation*, fourth edition ed., P. Hall, Ed. Prentice Hall International Series in Industrial and Systems Engineering, 2001.

[2] D. A. Menascé and V. A. Almeida, *Capacity Planning for Web Performance*. Prentice Hall, 1998.

[3] J. Flood, *Telecommunications Networks*, second edition ed. The Institution of Eletrical Engineers, 1997.

[4] W. E. Leland, M. S. Taqqu, W. Willinger, and D. V. Wilson, "On the self-similar nature of Ethernet traffic (extended version)," *IEEE/ACM Trans. Netw.*, vol. 2, no. 1, pp. 1–15, 1994.

[5] H. H and D. M. Lucsmtoni, "Markov modulated characterization of packetized voice and data traffic and related statistical multiplexer peformance," *IEEE Selected Areas in Communications*, vol. SAC-4, pp. 856–868, 1986.

[6] M. E. Crovella and A. Bestavros, "Self-similarity in World Wide Web traffic: evidence and possible causes," *IEEE/ACM Trans. Netw.*, vol. 5, no. 6, pp. 835–846, 1997.

[7] W.-B. Gong, Y. Liu, V. Misra, and D. Towsley, "Self-similarity and long range dependence on the internet: a second look at the evidence, origins and implications," *Computer Networks*, vol. 48, no. 3, pp. 377–399, 2005.

[8] W. Jiang and H. Schulzrinne, "Analysis of On-Off Patterns in VoIP and Their Effect on Voice Traffic Aggregation," *in Proceedings of 9th IEEE International Conference on Computer Communication Networks*, 2000.

[9] B. Bellalta, M. Oliver, and D. Rincón, "Capacity and traffic analysis of VoIP services over GPRS mobile networks," *Technical University of Catalonia, University Pompeu Fabra, Spain*, 2001.

[10] E. Casilari, H. Montes, and F. Sandoval, "Modelling of voice traffic over IP networks," *in Proc. of Communication Systems, Networks and Digital Signal Processsing (CSNDSP)*, 2002.

[11] W.-E. Chen, H.-N. Hung, and Y.-B. Lin, "Modeling voip call holding times for telecommunications," *IEEE Network*, vol. 21, p. pp. 22â28, November/December 2007.

[12] C. M. Pedroso, E. P. Ribeiro, and E. M. Munetiko, "Modelagem de Sistemas VoIP: Análise das Características da Sessão," *XXVI Simpósio Brasileiro de Telecomunicações SBrT09*, Outubro 2009.

[13] M. Menth, A. Binzenhöfer, and S. Mühleck, "Source models for speech traffic revisited," *IEEE/ACM Transactions on Networking*, vol. 17, no. 4, pp. 1042–1051, 2009.

[14] *A memory markov chain model for VBR traffic with strong positive correlations.* 16th Int. Teletraffic Congr. (ITC), Junho 1999, pp. 827-836.

[15] P. Barford and M. Crovella, "Generating representative Web workloads for network and server performance evaluation," *SIGMETRICS Perform. Eval. Rev.*, vol. 26, no. 1, pp. 151–160, 1998.

[16] J. Rosenberg, H. Schulzrinne, G. Camarillo, A. Johnston, J. Peterson, R.Sparks, M.Handley, and E. Schooler, "RFC 3261: Session initiation protocol," 2002.

[17] Schulzrinne, Casner, Frederick, and Jacobson, "RTP: A Transport Protocol for Real-Time Applications," 1998.

[18] G. ITU-T, "Pulse Code Modulation (PCM) of Voice Frequencies."

[19] ——, "Coding of Speech at 8kbit/s Using Conjugate-Structure Algebraic-Code-Excited Linear Prediction (CS-ACELP)."

[20] A. Orebaugh, G. Ramirez, J. Burke, and L. Pesce, "Wireshark & Ethereal Network Protocol Analyzer Toolkit (Jay Beale's Open Source Security)," Syngress Publishing, 2006.

[21] 3GPP, "3GPP recommentaion TR26.075: Performance Characterization of the AMR Speech Codec," 1999.

[22] ITU-T, "Q.1901 bearer independent call control," 2000.

[23] R Development Core Team, *R: A Language and Environment for Statistical Computing*, R Foundation for Statistical Computing, Vienna, Austria, 2009, ISBN 3-900051-07-0. [Online]. Available: http://www.R-project.org

[24] S. A. Klugman, H. H. Panjer, and G. E. Willmot, *Loss Models From Data to Decisions*, second edition ed., Wiley, Ed., 2004.

[25] R. Jain, *The Art of Computer System Performance Analysis: Techniques for Experimental Design, Measurement, Simulation and Modeling.* John Wiley and Sons, 1991.

[26] A. S. Tanenbaum, *Computer Networks*, Campus, Ed. Prentice Hall Professional Technical Reference, 2002.

[27] C. I. de Mattos, "Error Patterns for G.729 codec," 2010, available at http://www.eletrica.ufpr.br/pedroso/Tabela.html.

[28] G. E. P. Box and M. E. Muller, "A note on the generation of random normal deviates," vol. 29, 1958, pp. 610-611.

[29] "Bavarian Archive for Speech Signals (BAS) Verbmobil 6.1." 1996, http://www.phonetik.uni-muenchen.de/Bas/BasHomedeu.html.