

Pragmatic Approach For Estimating Wireless Broadband Traffic Using the Theory of Large Deviations

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Abstract—This paper proposes a methodology to predict wireless broadband network capacity based on effective bandwidth estimation. Former wireless network planning strategies were based on the estimation of the distribution of the number of users over the mobile network area. However, with the rapid spreading of wireless broadband networks and the increased number of services, the characteristics of user traffic have become an important matter due to the uniqueness of user profile. Furthermore, new wireless broadband networks are no longer based on circuit switching, but on packet switching technology. This paper applies the Large Deviations Theory to leverage estimation of the aggregated traffic intensity of several users. The approach was validated by analyzing known traffic traces of wireless broadband networks.

Index Terms— wireless broadband, effective bandwidth, capacity planning, aggregated traffic, mobility model.

I. INTRODUCTION

WITH the proliferation of wireless broadband networks over the last decades, we also saw an evolution in the technology that supports these networks from circuit switching into packet switching technology, propitiating a much wider choice of new multimedia and mobile services, and significantly diversifying traffic profile from one user to another. These changes made obsolete traditional methods of network capacity planning.

Aggregated traffic is the total traffic generated by simultaneous users of a given wireless broadband network. Traditional aggregated traffic estimation methods were based on short-range dependency models given the relatively homogenous user profiles traffic characteristics. However these methods are no longer suitable for use today because modern networks spot long-range dependency traffic characteristics, due to user's profiles that largely differs from one another.

In this context, each user now has at its disposal different packages of services. Thus, each user generates its own, unique, traffic footprint, and carries it along his trajectory within the wireless network coverage area. These changes have notorious implications in the network capacity planning process and lead us to devise a new platform for wireless broadband networks capacity planning.

Scientific literature presents several methods for wireless broadband network capacity planning [1][2][3][4]. The model described in [1] however, conveys characteristics of many

methods, and specifies a framework for capacity planning of wireless broadband networks, which would be composed by four modules: *Network Area Model*, *Markovian Mobility Model*, *Mobile Traffic Profile* and an additional *Traffic Estimator Module*, whose development pertains to this work.

With the inclusion of the Traffic Estimator Module, the framework is now complete and also takes into account users' mobility within network area and the fact that user's traffic profiles are heterogeneous among themselves. The framework presented in [1] will be employed throughout this work, and is briefly described in Section III.

By applying the Theory of Large Deviations to this framework, the present paper proposes a new method to estimate the aggregated traffic on wireless broadband networks.

The first objective of this work is to show that Theory of Large Deviation can be used to estimate the aggregate traffic intensity in wireless broadband networks.

The second objective is to integrate the mentioned aggregated traffic estimator module into the mobility model adopted in the framework, so that this framework would be able to estimate the aggregate traffic intensity in each part of the area of the wireless broadband network. The capabilities of the framework is therefore enhanced to better accomplish capacity planning for modern wireless broadband networks.

In order to achieve these objectives, we first analyze previous scientific works on effective bandwidth estimation methods and works on long-range dependent traffic models. Then we devise a method to estimate the aggregated traffic intensity and implemente this method in C++ language. To validate our method we use known, existing wireless broadband network traffic traces. First, we analyze these traces, using statistical analysis to obtain the bandwidth necessary, the aggregate traffic intensity and the mean deviation for each user. Then, using the C++ implementation of the proposed method, we again analyze the same trace data, this turn, applying the same aggregated traffic intensity and the same mean deviation obtained in the previous analysis.

Comparison between the bandwidth estimated by the Dembo method [5] and the aggregated traffic intensity yielded by new method revealed great parity between the results.

This comes to show that the Theory of Large Deviations is suitable for use in the estimation of aggregated traffic intensity, and able to create a modern platform for wireless broadband network capacity planning. For the sake of an organized presentation, the rest of this article is divided into the following sections: Section II describes the state-of-the-art

of packet network traffic treatment and effective bandwidth estimation; Section III describes the adopted framework [1] for capacity planning in modern wireless broadband networks, and presents the methodology for estimation of aggregated traffic intensity of different users into this framework; Section IV presents the validation of the new method through the analysis of real trace files, which has been used in several other scientific works, applying both, traditional methods and the new method, and comparing the results obtained; finally, Section V enlists the conclusions and contributions of this work.

II. STUDIES RELATED TO WIRELESS BROADBAND NETWORK CAPACITY PLANNING

This section briefly describes the main studies on wireless broadband network capacity planning, focused on three areas [2]:

- Mobility models,
- Traffic models,
- Radio channel models.

This study proposes an approach to broadband wireless network capacity planning based on users aggregated traffic intensity. Therefore, this section describes the main studies on mobility models, traffic models, and aggregated traffic treatment. We divide these former works into three subsections: Mobility Models, Long-Range Dependent Traffic Treatment, and Effective Bandwidth Estimation.

A. Mobility Models

These models are mathematical formulations used to describe the mobility behavior of users in a wireless mobile network. They are used for estimating users' trajectory and their distribution over the wireless network area. Thus, this subsection concisely describes previous main studies on mobility models. The work presented in [2] proposes a mobility model for Third Generation (3G) mobile network capacity planning, intended to support multimedia traffic. This is based on the analysis of the following factors:

- User mobility behavior,
- User mobility profile,
- Wireless network area.

It is also recommended in [2] that the services in use (voice, data, database access, video, etc.) must be accurately described. Several other studies were proposed following [2], such as those presented in [3], [4] and [6].

Although these works mentioned above propose multimedia network capacity planning or call admission control mechanisms for networks, they do not propose a way to estimate the traffic intensity to be generated within the wireless network area. The next subsection describes the main studies on long-range dependent traffic.

B. Treating Long-Range Dependent Traffic

With the development of broadband wireless technologies, it became noticeable that packet networks supporting the Internet could convey large amounts of different types of data,

such as audio, video, heavy files, video streams, etc. From that, we could also deduct that the Internet was a promising field to offer new services like video sharing, alongside with video conferences, IP telephony, e-commerce, e-business, e-learning, e-banking, video-surveillance, telemedicine and so many others.

In [7], Leland shows that traffic in packet networks has self-similarity characteristics and that the traditional queue models based on Poisson Processes are not appropriate to treat the traffic generated, because packet network traffic has long-range dependence features. After this study, the scientific community began to look for mathematical models that would take these self-similarity characteristics into account.

As Norros proposes in [8], self-similar traffic can be modeled by using Fractional Brownian Motion, while in [9], Jeong *et al.* uses the Fractional Gaussian Noise model and Wavelets to treat self-similar traffic. These models have proved to be more appropriate for packet network traffic treatment than Markovian queueing models. However, since packet network traffic is not entirely self-similar, it is necessary to indicate the self-similarity degree of the traffic. One way to measure the self-similarity of a phenomenon is by using the Hurst parameter H .

Huebner [10] shows that the heavy-tailed distribution functions can also be used to treat self-similar traffic. One advantage of treating self-similar traffic with these functions is their lower handling complexity compared to fractal-based models. In this class of function, Lognormal, Weibull and Pareto distributions stand out.

Gordon presents in [11] an analysis of the Pareto process to treat packet traffic with self-similar characteristics, and verifies the behavior of self-similar traffic models with arrival time defined by a Pareto distribution. In [12], Shortle proposes a technique to use the Equivalent Random Method in traffic models with arrival time defined by a hyper-exponential distribution. A round-robin scheduler for arrival traffic defined by a Pareto distribution is proposed by Reljin *et al.* in [13]. In [14], Xie *et al.* evaluates the performance of a queue with arrival time defined by a Pareto distribution applied to multimedia traffic of wireless networks.

An iterative method to achieve a Laplace transform approach, called Transform Approximation Method - TAM was described by Harris *et al.* in [15]. In [16], in order to improve the TAM, Fischer *et al.* proposed modifications to the version asserted by Harris *et al.* in [15]. Shortle also presents in [17] some difficulties related to the simulation of queues with service time defined by the Pareto distribution.

A representation of the Pareto function is presented in [18], where parameters α and β are estimated based on the Hurst parameter H . In the analysis carried out in [19] about the influence of parameter β on P/M/1 queue models, the representation developed in [18] is recommended because of the influence of parameter β on the decay of the Pareto function.

The major challenge in capacity planning of telecommunication network is to estimate the necessary bandwidth to meet traffic demand generated by a given number of users. The first telephony networks used circuit switching technologies, and

capacity planning was based on the estimation of channels to meet the needs of a certain number of users, using traditional Erlang equations.

As mentioned before, the traffic supported by networks based on packet switching technology has long-range characteristics. The scientific community has devised mathematical models which are no longer appropriate for traffic with these characteristics, among which, the fractional models and heavy-tailed functions stand out. Besides that, the traffic sources share the same communication channel. Consequently, the packet network traffic is formed by aggregating the traffic from a set of distinct sources, and this is a challenge to telecommunication network capacity planning as well. One of the ways of treating aggregated traffic in packet-based networks is the Theory of Large Deviations applied to the estimation of the effective bandwidth requirements, as discussed in [20], where an estimation of the capacity to support several multiplexed connections in an ATM network was proposed. The next subsection describes the main studies on the estimation of effective bandwidth using the Theory of Large Deviations.

C. Effective Bandwidth Estimation

According to Rabinovitch [5], effective bandwidth refers to the traffic stream measure used in dimensioning modern telecommunication network based on packet switching technologies. In these technologies, two or more traffic flows are multiplexed into a stream of transmission that is common to all flows. Therefore, it is important to estimate the amount of flows that can be served by the bandwidth, and which availability is given directly by the transmission means without violating the service level restrictions of each flow.

In [21], Kelly presents an equation to estimate effective bandwidth of traffic source and discuss some aspects of effective bandwidth estimation. Effective bandwidth is computed as

$$\alpha(s, t) = \frac{1}{s t} \log E \{ \exp (s X[0, t]) \}, \quad (1)$$

for $0 < s, t < \infty$, in which $X[0, t]$ is the arrival process that characterizes traffic volume. The parameter s represents the spatial scale and indicates the multiplexing degree. High values of s denote a low multiplexing degree and means that the traffic effective bandwidth is close to the maximum traffic flow and, therefore, just a few flows can be served. On the other hand, low values of s indicate a high multiplexing degree, that is to say that the traffic effective bandwidth is in the vicinity of the average, so a large amount of flows can be served [22].

The parameter t in expression (1) is the most likely period of time that the system will be busy before there is an overflow and, consequently, the minimum time scale that the traffic needs to be observed so as to analyze overflow events. High values of t indicate that the overflow is observed for large time scales, whereas low values of t indicate that the overflow is seen in small time scales. Therefore, we can observe that parameters s and t depend on the characteristics of the supported traffic. The most relevant point in expression (1) is the definition of the parameter s . As recommended by

Kaj in [22], s can be computed as

$$s = \frac{-\log p}{b}, \quad (2)$$

where b is the buffer size and p is the probability of overflow. The relation between p and b is defined as

$$\Pr\{L > b\} < p, \quad (3)$$

where L is quantity of data traffic that arrives at the buffer.

The statistical properties of the effective bandwidth equation are analyzed in depth by Rabinovitch in [5], and the probability of overflow of N sources of traffic is described as

$$\log \Pr\{\text{overflow}\} \approx e^{-N I}. \quad (4)$$

where I is the asymptotic rate function for capacity c and buffer size b , and is given by

$$I = \sup_t \min_s \{ s t [N \alpha_j \alpha(s, t)] - s (C t + B) \}, \quad (5)$$

where $B = N \times b$ and $C = N \times c$.

The asymptotic rate function I can be alternatively expressed as [20]

$$I = \inf_{t > 0} t \lambda^*(t^{-1}). \quad (6)$$

which uses the Legendre-Fenchel transform of λ , denoted by λ^* , as described in the study by Courcorbetis *et al.* in [23]. The investigation of the principle of large deviations applied to the estimation of effective bandwidth has been the aim of several studies. Kelly proposes [21] to use the effective bandwidth to meet the demand of aggregated traffic of N homogeneous sources, denoted by eb_N , given by

$$eb_N = N \times \alpha(s, t). \quad (7)$$

According to Kelly in [21], when there are heterogeneous traffic sources in the networks, the effective bandwidth of M heterogeneous sources is estimated by the sum of effective bandwidths of each source. In [21], the effective bandwidth for heterogeneous sources, denoted by eb_M , is computed as

$$eb_M = \sum_{i=1}^M \alpha_i(s_i, t_i). \quad (8)$$

In order to estimate the effective bandwidth based on traffic analysis, we consider in this work two methods previously proposed to analyze trace files: the Dembo estimator and the resampling methods [5]. The Dembo estimator has been widely used to estimate the effective bandwidth. In order to guarantee the appropriate use of this method, we need a set of traffic trace samples. According to Dembo estimator, the effective bandwidth is given by

$$eb_D = \frac{1}{s t} \log \left(\frac{1}{\lfloor T/t \rfloor} \right) \sum_{i=1}^{\lfloor T/t \rfloor} \exp (s X[i-t, i]), \quad (9)$$

where T is the trace period, and $\lfloor x \rfloor$ indicates the largest integer smaller than or equal to x . Thus, the Dembo estimator is an iterative method that replaces the traffic distribution function with the traffic volume described by the trace samples.

In [20], Duffield *et al.* use the work done by Kelly in [21] to estimate the economy of scale in multiplexers, aiming at minimizing cell loss probability in ATM switching. Courcoubetis *et al.*, in [23], describe the implications of applying several asymptotic sources and the theory of effective bandwidth in traffic engineering. The studies presented by Gibbens [24] and Duffield [25] applied the effective bandwidth theory to real traffic network analysis. Improving the study presented in [20], Duffield [25] establishes a relation between cost and quality of services for aggregated traffic networks.

One of the procedures we use in this work is described in [26]. The model for estimating the effective bandwidth, called *effective channel model*, is based on the analysis of the characteristics of the channel and the Theory of Large Deviations. This model estimates the amount of effective bandwidth available in a channel for a given time interval, with accuracy ϵ , as

$$\bar{S}_{\Delta}^{\epsilon}(\tau) = \sup_{s < 0} \left\{ \tau \alpha_c(s, \tau) - \frac{\log \epsilon}{s} \right\}, \quad (10)$$

where $\alpha_c(s, \tau)$ is the effective bandwidth defined by equation (1) for a channel model $C[t]$, defined as

$$C[t] = c \int_0^1 [1 - \Theta(x)] dx, \quad (11)$$

where

$$\Theta(t) = \begin{cases} \text{PER}[\text{SNR}(t)] & \text{if } \text{SNR}(t) \geq \Delta \\ 1 & \text{if } \text{SNR}(t) < \Delta \end{cases}, \quad (12)$$

and SNR is the signal-to-noise ratio at the receiver at time t , and $\text{PER}[\text{SNR}(t)]$ denotes the packet error rate at time instant t . The term c in (11) is the nominal data rate of the channel.

However, there is a better approach to the effective bandwidth evaluation in virtue of the definition of the global scale parameter for traffic characterized through multi-fractal processes [27]. We assert that this is a substantial improvement to the model proposed by Norros in [8].

Tang [28] points out that the aggregated network traffic converges into long-range dependent α -stable processes. The authors of [29] reported an empirical algorithm for effective bandwidth estimation based on the binary search algorithm.

Likewise in other works about effective bandwidth estimation, the algorithm presented in [29] by Davy *et al.* is driven by QoS support in Call Admission Control. They draw our attention to avoid QoS violation, and come to the conclusion that the effective bandwidth theory is relevant among other things, for providing QoS on packet networks. In their analysis of the impact of the user mobility over the aggregated traffic behavior in wireless networks, they conclude that the traffic behaves self-similarly [29] the same as in fixed networks.

Basgeet *et al.* [30] state that the theory of effective bandwidth can be used to model the relationship between cognitive traffic rate and cognitive user queue distribution. In their investigation about call admission control mechanisms, Laourine *et al.* [31] propose a model for cross-layer effective bandwidth to be applied in CDMA networks.

Previous studies on estimation of effective bandwidth have shown that the Theory of Large Deviations is a very plausible

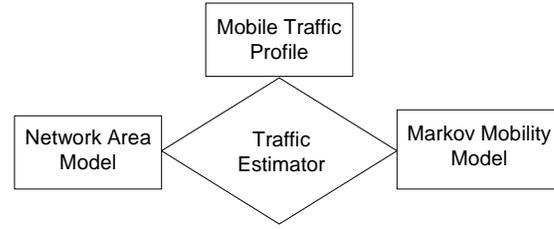


Fig. 1. Framework Structure proposed in [1].

way to estimate the traffic intensity in a wireless network area. However, a key problem with much of the literature regarding to this matter is that they do not associate the effective bandwidth estimation to a model that represents the user spatial distribution over the wireless network area. In the next section we describe a way to apply the Theory of Large Deviations to estimate the effective bandwidth in wireless broadband network capacity planning.

III. APPLICATION OF THE THEORY OF LARGE DEVIATIONS TO ESTIMATE TRAFFIC INTENSITY IN WIRELESS BROADBAND NETWORKS

A. Framework for planning wireless broadband network capacity

In [1], a framework for capacity planning of wireless broadband network based on the estimation of the traffic generated by users was proposed. This framework has four components (see Figure 1):

- **Network Area Model:** model for describing the network area according to the Manhattan-Grid, which splits the area into grids. The Manhattan-Grid model is also used in other studies, such as [2]. It describes the characteristics of the network area, such as geographical aspects, constructions, movement attraction points and ways of access.
- **Mobile Traffic Profile:** this module contains information about users and available services. User profiles are defined, and each one is associated to a traffic profile.
- **Markov Mobility Model:** it is the probabilistic formulation used to estimate the variation of user distribution over a wireless network area, and is described as [1]:

$$\begin{aligned} N_i(t+1, \rho) &= N_i(t, \rho) + \\ &- \sum_{j, C_j \in S_{adj}^i} N_j(t, \rho) P_{Mout(i)}(j, t, \rho) + \\ &+ \sum_{j, C_j \in S_{adj}^i} N_j(t, \rho) P_{Min(i)}(j, t, \rho), \end{aligned} \quad (13)$$

where

- $N_i(t, \rho)$ is the amount of ρ -profile users, at time t , in grid i ,
- $P_{Min(i)}(j, t, \rho)$ is the probability of arrival of ρ -profile users coming from the adjacent grid j , at time t , to grid i ,
- $P_{Mout(i)}(j, t, \rho)$ is the exit probability of ρ -profile users from grid i into the adjacent grid j , at time t .

- **Traffic Estimator:** this module integrates the other modules and has two functions: 1) to analyze the information from the modules Network Area Model and Mobile Traffic Profile, in order to estimate the probabilities used in the mobility model, and 2) to estimate the aggregated traffic generated by several users. This method is described in Section IV.

The probabilities used in the mobility model can be estimated using [1]

$$P_{Mout(i)}(j, t, \omega) = \frac{\sum_{l \in K_j} \kappa_{l,t,\omega} + \sum_{l \in V_j} s_{l,t,\omega}}{\sum_{l \in N} \sum_{n \in K_l} \kappa_{n,t,\omega} + \sum_{l \in N} \sum_{n \in V_j} s_{n,t,\omega}} \times (1 - P_{res(i)}), \quad (14)$$

where

- K_l is the set of movement attraction points of a grid,
- κ is the weight of a particular movement attraction point for time instant t and profile ω ,
- V_l is the set of ways from grid i to grid j ,
- s is the total weight of the access ways from grid i to grid j ,
- $P_{res(i)}$ is the probability of users to remain in grid i at time t .

Expression (14) is applied over each pair of adjacent grids composing the area to calculate the user distribution probabilities used by the mobility model of the framework. The results of the probability estimation exposed in [1] were obtained from the first implementation of the Markov Mobility Model. To validate the probability estimation method and the Mobility Model, these results are compared on a framework prototype with data gathered from trace files showing coherence.

After the results are validated, it is necessary to estimate the traffic intensity in the wireless network area. Traffic on broadband networks is the result of aggregating traffic of several users, whose characteristics are found in the Mobile Traffic Profile. Based on the studies on Theory of Large Deviations applied to effective bandwidth estimation, the next subsection presents a method for estimating traffic intensity based on several traffic profiles.

B. Effective Bandwidth Estimation For Traffic Profiles

Based on the works presented in the previous sections, the aggregated traffic estimation model employed in this work uses the theory of large deviations for telecommunications. In this section we propose the use of the effective bandwidth formulation to predict traffic intensity.

The effective bandwidth for a source, described in expression (1), requires parameters already used in traffic prediction methods well known to the scientific community, such as mean rate and standard deviation rate. The s and t parameters can be obtained by trace file analysis of similar traffic. The method proposed in this section consists of using the effective bandwidth representation presented in expression (8) for aggregated traffic prediction of several applications related to one traffic profile. Thus, the expression for estimating the total traffic

eb_{all} is described by:

$$eb_{all} = \sum_{i=1}^M \sum_j^{A_i} \alpha_{i,j}(s, t), \quad (15)$$

where

- M is the size of the set of traffic profiles,
- A_i is the set of services related to profile i ,
- n_i is the number of users of profile i ,
- $\alpha_{i,j}(s, t)$ is the effective bandwidth of service j related to user profile i .

Thus, according to the proposed framework, the traffic estimation in each part of the wireless network will be obtained by the following procedure:

- Estimation of parameter s for a particular traffic profile,
- Obtainment of the parameters for mean and standard deviation of the traffic modeling function, using some type of estimator, such as the Dembo estimator,
- Estimation of the effective bandwidth for each traffic profile,
- Sum of the effective bandwidth of the of users in each profile,
- Sum of the total bandwidth of all profiles.

Regarding the probability distribution function that characterizes the traffic of a source, it is recommended a heavy-tailed distribution function and/or fractal function, since traffic in packet networks present a long-range dependence characteristic.

C. Integration of the Traffic Estimator Module into the Framework

The integration of the module described in the previous subsection into the proposed framework [1] consists of two steps: 1) By evaluating the parameters to be used, and 2) by applying the traffic estimation technique to the wireless network area.

The Traffic Estimation module is processed after the mobile traffic profiles were defined and the mobility model was processed, evaluating the distribution of users over the wireless network area. The parameters to be used as profile, mean rate and standard deviation of the services related to each profile are generated by the Mobile Traffic Profile module. This information can be found in structured files to be read by the Traffic Estimation module. After obtaining the data, the Traffic Estimator is executed over each part of the specified network area.

Previous studies on performance evaluation and modeling of networks have often used the formulation presented in this section. However, it is necessary to verify how appropriate this formulation is for the framework proposed in [1]. In order to verify the applicability of this work, the next section describes the implementation of the proposed bandwidth estimation method by building a Traffic Estimator module for the framework. Results obtained from the analysis of trace files are also presented.

The integration of the method for effective bandwidth estimation for traffic profiles presented in the previous section,

with the mobility model framework [1] is accomplished by expressions (13) and (15). Expression (13) estimates the number of users with similar profiles at a given moment. By applying this expressions to all traffic profiles, we obtain the quantity of users in each profile, forming the set M , which is used in equation (15) to estimate the aggregate traffic intensity. The aggregated traffic intensity and the mean deviation are calculated in the Mobile Traffic Profile module.

The next section presents details of the implementation of the aggregate traffic intensity estimation method, together with some results obtained from traffic traces.

IV. IMPLEMENTATIONS AND RESULTS

The implementation of the traffic estimation module aims to verify how appropriate it is this estimation approach for wireless networks supporting long-range dependent traffic.

The estimation method was implemented using C++ language, and is based on two classes: `Trace` and `Effective_Bandwidth`.

The `Trace` class analyzes the trace files and generates another one with the following data: average and standard deviation of the packet size, average and standard deviation of the traffic rate, and peak rate.

The class `Effective_Bandwidth` estimates the effective bandwidth as proposed in Section III, where the input data can be structured according to a trace-class output file, or according to a traffic profile data file previously defined.

In order to validate the effective integration of the bandwidth estimation with the framework proposed in [1] as a functionality, trace files related to data traffic were analyzed. These files are in tcpdump format and refer to a network based on CDMA2000 1x-EV-DO technology, which provides 2.4 Mbps for downlink. Sixteen users were monitored using laptops in the city of Seoul, South Korea. The tool tshark was used to read and export the data to files in text format. These trace files are found in the website of CRAWDAD community [32], and have already been used in other works, such as [33]. These trace files correspond to approximately eight hours of monitoring. According to studies on effective bandwidth estimation, such as [5], [22] and [20], a particular source value lies between the mean rate and peak rate. Consequently, the expected effective bandwidth must be between these two values.

The traffic used in this analysis corresponds to a downlink data traffic using TCP/IP architecture. Therefore, it is necessary to consider the TCP and IP headings as part of the transferred information. Firstly, it was performed an individual analysis of the effective bandwidth for the traffic corresponding to each user (16 of them). Based on the Dembo estimator technique described in [10], an estimation of effective bandwidth of the trace files was performed, where a value for t was defined and a value for s was estimated given a particular effective bandwidth. As suggested in [34], the value chosen for the determined effective bandwidth is the mean rate obtained from the trace files and t is fixed at 0.1 seconds. The value estimated for s was obtained from expression (2). In order to create a scenario where the overflow conditions

TABLE I
AGGREGATED TRAFFIC: DEMBO METHOD VS. EFFECTIVE BANDWIDTH
(BITS PER SECOND)

User	Peak rate	Mean rate	Dembo	Proposed method
1	24192	9700	9600.9	9701
2	25704	7174	7094.0	7174
3	25416	10493	10480.9	10494
4	26928	10352	10246.5	10354
5	11968	5437	5369.6	5437
6	13480	5119	5233.7	5237
7	13480	6120	5978.4	6120
8	27216	6337	6223.1	6338
9	20912	7238	7181.5	7238
10	22680	6428	6305.9	6428
11	16472	6572	6551.7	6572
12	11968	6292	6258.4	6292
13	17984	6541	6512.6	6541
14	11968	6109	6081.0	6109
15	17952	6732	6620.2	6732
16	22680	6585	6476.7	6586

were minimized, a buffer size of 10^8 and block probability equal to 10^{-9} were considered, resulting in $s = 1.42 \times 10^{-7}$. Considering that the chosen value of s is close to zero, the estimated effective bandwidth was expected to be close to the mean rate.

Using the trace analysis, the mean and variance were estimated and used to calculate the bandwidth expression. In this work, the effective bandwidth as calculated using the expression [5]

$$eb(s, t) = \mu + \frac{s\sigma^2}{2}t^{2H-1}, \quad (16)$$

for $0 < s, t < \infty$, where μ is the mean value, σ^2 is the traffic variance and H is the Hurst parameter, which was set to 0.8 for this simulation. It should be noted that expression (16) evaluates the effective bandwidth when the Fractal Brownian Motion model is assumed.

Table I compares the aggregated traffic estimated using the Dembo method with that estimated using the effective bandwidth method. The aggregated traffic, in bits per second, was estimated using the same values for mean and peak rate in both techniques. As expected, the results in Table I indicate that the estimated effective bandwidth is close to the mean with values between the mean rate and the peak rate for each user. Particularly for this analysis, the effective bandwidth equation proved to be more effective than the Dembo estimator.

Figure 2 shows a graph comparing the effective bandwidth estimation of the traces, obtained by applying the Dembo estimator and the method proposed by this work. As we can see, the results from the proposed method are very close to those from the trace files. This close match is expected, because of the low value of s . The effective bandwidth allows traffic intensity estimation from different sources, which is very important in capacity planning of broadband networks. The correct adjustment of parameters s and t depends on knowledge of traffic characteristics.

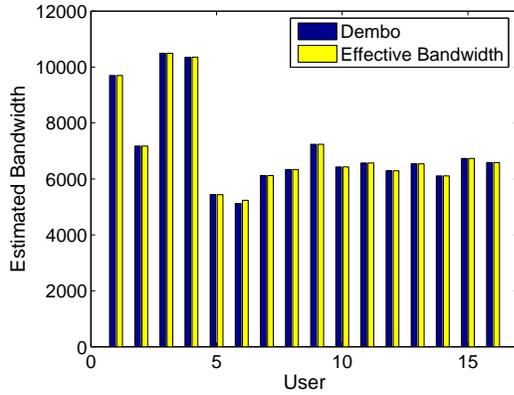


Fig. 2. Aggregated Traffic: Dembo Method vs. Effective Bandwidth method.

TABLE II
COMPARISON BETWEEN THE PROPOSED METHOD AND EMPIRICAL METHOD [29].

Estimated Bandwidth (b/s)		H	Mean Rate (b/s)	Peak Rate (b/s)	Standard Deviation (b/s)
Empirical [29]	Proposed Method				
66049	66403	0.55	273	131824	144
66053	67920	0.56	281	131824	150
3689	3577	0.54	145	7232	32
32569	30437	0.70	320	64816	153
3460	3364	0.55	135	6784	32
3202	4007	0.60	196	6208	40
12751	15608	0.80	381	593232	147
298635	298271	0.77	4038	593232	590

Next, we compare the results from the proposed method with the results presented on [29], where the authors propose an algorithm based on binary search and trace analysis to estimate the bandwidth for aggregated traffic. In this work, the authors used trace files from a WiMAX network, also used in [35], and estimated bandwidth based on the acceptable maximum delay time, the target proportion of traffic allowed to exceed acceptable maximum delay time, and the percentage and margin of accuracy in order to find the effective bandwidth value for a particular QoS target.

In [29] the maximum delay time and the delay probability were set to 10^{-3} seconds and 0.5%, respectively. The values for t and s were adjusted to 10^{-3} seconds and 2.99, respectively. Using these values, we estimated the bandwidth for traces considered. The Hurst parameter H , the mean rate and the standard deviation of the trace files were estimated to be used as input parameters for the proposed bandwidth estimation method. Particularly, the parameter H was estimated by applying the R/S statistic [24] over trace files. The results are presented in Table 2, and show that the proposed method and the empirical method from [29] lead to similar results. Table II also shows the corresponding values of Hurst parameter, mean and peak rates and standard deviation of the traffic.

V. CONCLUSIONS

A literature review revealed the lack of a method for estimating the aggregated traffic intensity from users of mobile services with different profiles, suitable for capacity planning of wireless broadband networks with long-range duration traffic characteristics. This present work proposed the application of the Theory of Large Deviations to develop a platform for capacity planning of modern wireless broadband networks.

The Theory of Large Deviations has been long studied and successfully applied to the estimation of effective bandwidth and to call admission control mechanisms. The studies in this work indicate that the Theory of Large Deviations can also be used to estimate the aggregated traffic intensity in wireless broadband networks, as discussed in Section III. The contributions of this work can be summarized as follows:

- We demonstrated that the Theory of Large Deviations can be an efficient tool for the estimation of the aggregated traffic intensity,
- we introduced a methodology to estimate the aggregated traffic intensity for mobile users with different traffic profiles,
- We describe a platform for network capacity planning, based on the Theory of Large Deviations.

A few suggestions for future works are listed below:

- To incorporate the effective bandwidth method into the channel model adopted in the framework,
- To develop other methods for processing the aggregated traffic,
- To integrate the features of the wireless networks into the channel model characteristics [2].

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