Classification and comparison of modelling strategies for VBR video traffic

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In this paper we propose a framework to classify and compare existing video traffic models. The classification is performed according to the statistics which the models intend to fit: first order statistics (PDF or Probability Distribution Function), Short Range Dependence (SRD) or Long Range Dependence (LRD). After a thorough comparison of the models in a queue, using real MPEG traces, we conclude that, for realistic scenarios, a good fit of the PDF is essential while the effects of SRD have a secondary importance and LRD could be neglected. Consequently, special attention is devoted to the election of a standard PDF which can properly describe video traffic burstiness. On the other hand, we also investigate the problem of "starvation" by means of which LRD properties, which have no impact on real-time video services, could affect the quality of other lower priority services which are conveyed on the same network. In particular, we study the quality of real HTTP (HyperText Transfer Protocol) traces being multiplexed on the same link as video traffic.

1. INTRODUCTION

Video traffic modelling has become a key issue due to the increasing importance of digital video services within multimedia networks. Adequate video traffic models are needed to solve the still open problems that multimedia traffic management arise, such as bandwidth allocation, policing functions or admission controls. Moreover, video transmissions are especially critical if we consider the high bandwidths and the strict quality parameters (delay, losses) that they normally require. Video signal can be encoded and compressed in two ways: with variable quality and constant bit rate (CBR) or otherwise, with constant quality at the price of changing the bit rate. These Variable Bit Rate (VBR) video signals will benefit from statistical multiplexing that protocols such as ATM provide, optimising the utilisation of the network and achieving a better ratio quality/required bandwidth. However, in contrast with CBR traffic, which offers a constant flow to the network, VBR compression imposes on traffic a more complex statistical nature, as it depends on the images and sequences that are being transmitted.

In this work we analyse the impact of different VBR video traffic characteristics on queuing performance. We compare the behaviour of different models to determine which statistical properties are crucial for modelling purposes and which could be neglected despite of their actual existence in video signals. We show that under high channel utilisation and large buffer sizes, Long Range Dependence (LRD) is the most relevant property to match. On the contrary, with small buffers and low levels of channel occupation, Probability Distribution Function (PDF) and, secondarily, short range dependence (SRD) must be captured to approximate Quality of Services (QoS) requirements, essentially losses, average delay and jitter. In any case, we prove that LRD could be necessary to model if we consider the multiplexing of other services, such as data traffic, which are more delay-tolerant and admit buffering.

2. VBR VIDEO TRAFFIC MODELLING

The aim of a video compression scheme is to reduce the bandwidth requirements for the video traffic by removing part of the temporal and spatial redundancies that an uncompressed video signal exhibits. The consequence of VBR encoding is that video traffic is strongly related to the underlying mechanisms in the generation of video sequence. The most relevant characteristics that video nature incorporates to the generated traffic are:

- A huge variability in the bit rate, which is determined by the variability in the image complexity and the degree of motion of the filmed objects and the camera. This phenomenon can be detected analysing the PDF or its derivative the pdf (probability density function) of the number of bits generated by the encoder within a fixed period of time (e.g.: a frame).
- Short term correlation, motivated by the resemblance between the contents of frames within the same scene. This effect is reflected in high values of the first autocorrelation coefficients of the sequence.
- Long term correlation between frames belonging to separated scenes with similar levels of motion and image complexity. This LRD are reflected in a slow (hyperbolic) decay of the autocorrelation function, which is significant even for lags longer than several minutes. LRD is normally related to a certain degree of self-similarity, that is, the variability over a wide range of time scales.

Although the interest of video traffic characterisation has motivated the appearance of a wide set of models, not much attention has been devoted to classify and compare the present modelling strategies in a systematic way. In order to define a framework to evaluate the nature and the possibilities of different models, we propose to establish a classification according to the statistical property (PDF, SRD and LRD) that they intend to match. This classification is depicted in figure 1. Dark circles include these three generic statistics while dashed circles, which separate the different models, intersect them depending on the characteristic the models fit. As it can be drown from the figure there exist models that simultaneously imitate two or three types of statistics.

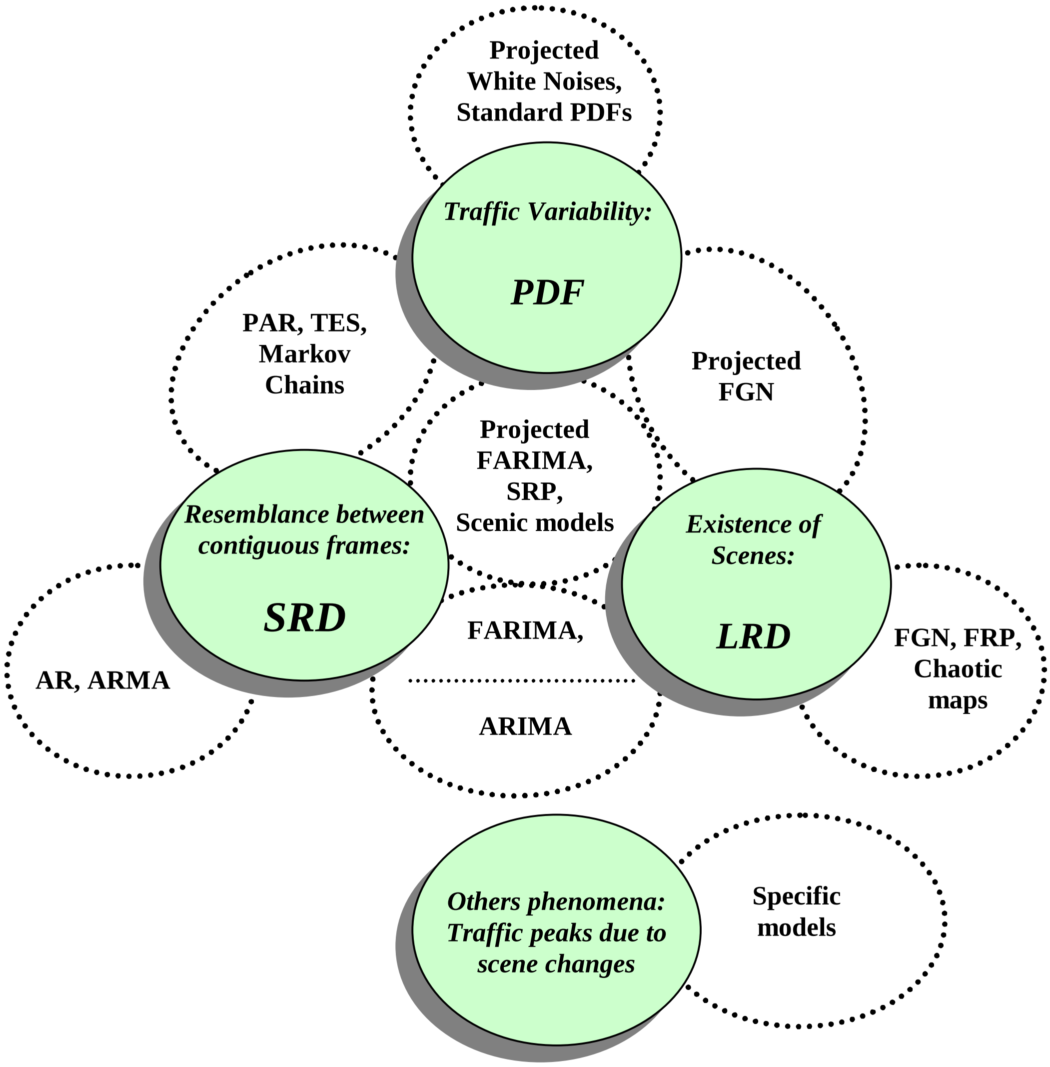


Figure 1. Classification of VBR Video traffic models

The different models that the bibliography proposes can be categorized using the previous scheme:

1. The simplest solution to roughly approximate the bell-shaped pdf of video traffic is generating a gaussian noise with the same mean and variance of the video sample to imitate. As the PDF of video signals is normally skewed to the left (lowest values), Gamma, Weibull or Lognormal distribution functions have also been proposed [1] for a more accurate matching of the shape of the PDF. Finally, empirical models perform a better fit at the expense of needing a wide set of parameters. These models project a white noise, uniformly distributed between 0 and 1, on the inverse distribution function to match, which must be previously calculated by estimating the histogram of the signal. So, the fit will be as accurate as the estimation of the histogram.

2. To cope with the SRD, Markov chains [2], Autorregresive (AR) and Autorregresive Moving Average (ARMA) filters [3] have been normally utilised. In general, these models are

characterized by an exponentially (quick) decaying autocorrelation which fits that of the real series just for the first lags. SRD and PDF are simultaneously matched by Transform Expand Sample (TES) [4] and Projected Autorregresive (PAR) models [3] which project an autocorrelated signal on the target PDF to achieve an accurate fit of the first order statistics.

3. The LRD of a signal [4] can be defined via a single value called the Hurst parameter (H), which is related to the decay rate of the autocorrelation function when lags tend to infinity. The range of possible values for H is [0.5 1], where 0.5 indicates that there is no LRD while the degree of LRD (or self-similarity) in the signal increases as H approximates to 1.

A common method to generate pure self-similar signals, with a desired value of H, is the Fractal Gaussian Noise (FGN) [1]. Chaotic Maps and Fractal Renewal Processes [6] have also been proposed to synthesize long term self-similar traffic.

Fractional Integrated ARMA (FARIMA) models are commonly used to adjust both LRD and SRD. As in the case of TES or PAR models, FARIMA or FGN signals can be projected to improve the fit of the PDF at the cost of a slight deformation of the correlation properties. Spatial Renewal Processes (SRP) are able to simultaneously capture [7] any PDF and any decaying autocorrelation, including hyperbolic (LRD) decays.

On the other hand, scene oriented models [7] [8] [9] constitute an specific approach to video traffic modelling. These structural models analyse traffic belonging to different scene types separately, so that they usually consist of two layers: a higher layer models scene lengths and switching between scenes, whereas a lower layer imitates the traffic within each particular scene. Statistically these models could be situated between SRD and LRD modelling, as they are not strictly self-similar and just capture long term behaviour for a finite range of time scales.

Apart from all these models, Figure 1 also include (intersecting a different dark circle) those specific models which are designed to adjust other phenomena of particular video series. The most remarkable models in this group are those which incorporate some statistical mechanism to imitate traffic peaks existing in video signal due to scene changes. They usually consist of Markov chains with a special state modelling these peaks.

Despite of this large variety of video traffic models, no thorough comparisons between them have been performed in the literature. In order to evaluate the impact of each statistical characteristic in network performance, we analyse the behaviour in a queue of all these families of models when compared with those of two real MPEG traces.

3. COMPARISON OF MODEL PERFORMANCES

For comparison purposes, we choose two real MPEG sources. The first one is the whole film "Star Wars" which is widely used in the literature [1] [3] [5] [8] [11] to evaluate modelling and management schemes. The other series is a long trace of several 30 minute sequences of different video signals, containing TV programs, news, films, sports and cartoons, compressed with the same MPEG encoder in the University of Wurzburg (Germany). For both traces we considered the GOP or Group of Pictures (about 12 frames) as the time scale of the series. A frame level model should consider the deterministic GOP pattern to split the traffic between the three different types of MPEG frames (I or Intraframe, P or Predictive and B or Bidirectional).

To study the influence and the importance of the different statistics we utilise a wide set of models, representing all the possible groups defined in figure 1:

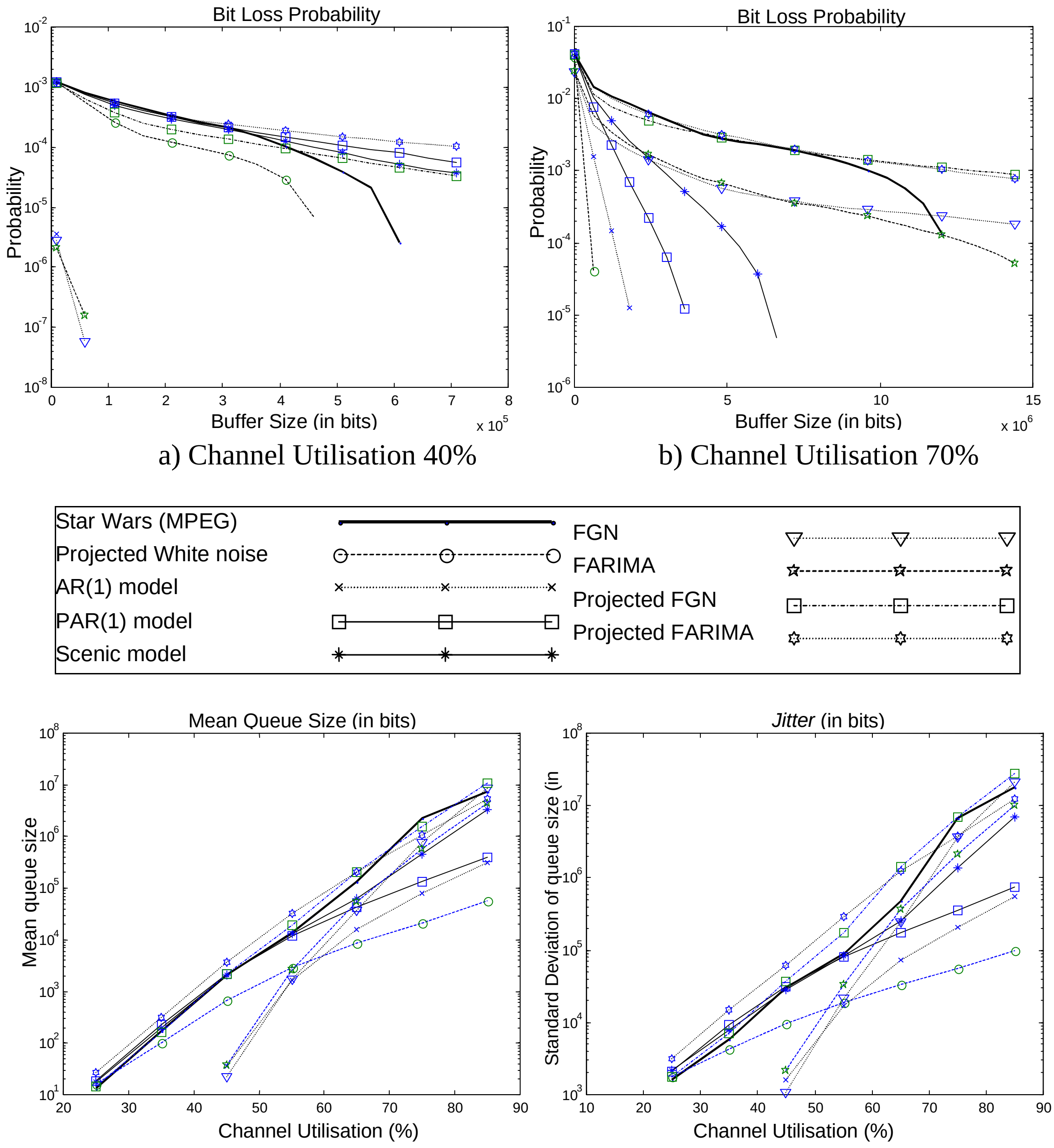
- A white (uncorrelated) noise projected on the target PDF, which is estimated using a histogram of 30 bins.
- An AR(1) model designed to match the first autocorrelation coefficient. This order is chosen following the partial autocorrelation and Akaike criteria. The output PDF of this model is gaussian.
- An improved PAR(1), proposed by the authors in [3], matching the PDF and the SRD.
- A scene oriented model, also proposed in [3], which takes into account 3 different types of scenes. The switching between the scenes follows a Markov process. The traffic within each scene is generated following a PAR model.
- A FGN with the same H parameter of the actual series. Using different estimators (variance plot, R/S plot, periodogram and Whittle) an approximate value of 0.90 was estimated for H in the case of "Star Wars", while for the signal from Wurzburg H was found to be 0.95. These results indicate that the traces own a high degree of LRD.
- A FARIMA model with gaussian output, adjusting the mean, the variance, H and the autocorrelation for the first lag of the series. The orders of the AR(p) and MA(q) sections are chosen to be 1 and 0 respectively following the same criteria as for the AR process.
- We also propose to project the two previous models (FGN and FARIMA) to approximate the target PDF. These projections are performed at the cost of a slight distortion of the correlation matching.

All the models are designed to match the mean rate and the standard deviation of the series, independently of the other statistics they fit.

More than $2 \cdot 10^6$ samples (GOPs) were generated for each model and buffered in a simulated queue with deterministic time service. The bit loss probabilities for all the models adjusting the series "Star Wars" are depicted in figures 2.a and 2.b for channel occupations of 40% and 70%, respectively. Under low occupations those models that accurately adjust the PDF perform a good fit of the losses while AR, FGN and FARIMA, which only adjust correlation properties, seriously underestimate them. Only when buffer size increases, projected FARIMA and projected FGN improve the fitting of PAR and projected white noise. On the other hand, under high occupations and large buffer sizes, figure 2.b proves that LRD becomes the most determinant statistics to match, independently of the shape of the pdf. Nevertheless it must be observed that projected FARIMA exhibits the best fitting under all conditions. In all cases scene oriented model occupies intermediate position between SRD and LRD models. Identical conclusions can be drawn when considering the series from Wurzburg (not depicted here).

Figures 2.c and 2.d show, as a function of channel utilisation, the mean value and the standard deviation of the queue size (regarded as measurements of mean delay and jitter, respectively). These results prove the same tendencies that were detected for losses: under low occupations the critical parameter to imitate is the PDF. On the contrary, LRD models with gaussian outputs tend to converge to the real trace as the utilisation increases, while firstly uncorrelated model, and secondly SRD models progressively diverge from reality.

It must be remarked that most video services, specially real-time applications, will demand strict QoS requirements, that is, very small loss rates and very low jitters (in the order of some ms.). This implies that small buffers and low occupations correspond to a realistic scenario of a video service transmission. Consequently, just projected or SRD models will be enough to fully characterize VBR video traffic.

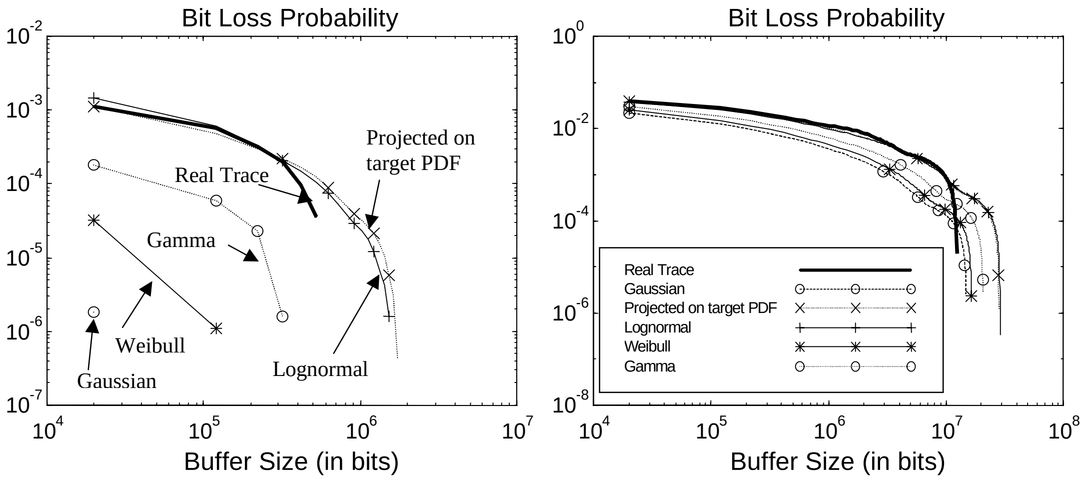


c) Mean queue size

d) Jitter

Figure 2. Comparison of model performances.

As it has been pointed out before, projecting a signal on the target PDF requires to calculate, sample and store the histogram of the real trace. Thus, this projection seriously affects the parsimony and transportability of the model. To overcome these drawbacks, the use of other standard distributions is usually contemplated. The main advantage of these standard distributions is that they can be described in terms of just one or two parameters.



a) Channel Utilisation 40% b) Channel Utilisation 70%

Figure 3. Performance of FARIMA models projected on different standard distributions.

Figure 3 compares the losses of FARIMA models whose outputs are projected on the most commonly used standard distributions. The parameters of distributions are chosen to fit both the mean rate and the standard deviation of the real trace. Maximum Likelihood Estimators (MLE) could also have been utilised, offering similar results. Figure 3.a shows that under low channel utilisations (40%), for which a proper fit of PDF is fundamental, the log-normal distribution outperforms the rest of standard PDFs (Gamma, Weibull and gaussian), approximating with accuracy the results given by the projection on the target PDF and, consequently, the losses suffered by the real trace. Log-normal distribution, together with the gamma, has also been shown to be the best distributions to fit the traces from Wurzburg. For a higher utilisation (70%) Figure 3.b proves that the utilised distribution is almost indifferent for losses. This is due to the fact that for high channel utilisation the buffer smoothes the traffic input so that the queueing performance (losses and delays) is completely determined by the autocorrelation structure of the incoming traffic [11]. Therefore, FARIMA log-normal model offers a compact representation of the real traffic, which is able to approximate the queuing parameters for a wide range of channel utilisations and buffer sizes. The models just require two parameters to define the log-normal distribution (these parameters can be easily derived from the mean rate and the standard deviation), H to describe the LRD and the ARMA coefficients of the FARIMA filter (in this case just one coefficient for the AR component of the filter).

4. LRD AND THE PROBLEM OF STARVATION

In the previous section it has been argued that, under realistic scenarios for a video transmission, with minimum buffering and low channel utilisation, LRD has no effect on video performance and quality of service. This conclusion is coherent with other studies such as [2] [6] [9] [11]. However, no attention has been paid to the fact that video traffic, in an asynchronous network, will share the link with other non real-time services, whose QoS could be affected by the LRD that video exhibits. As LRD implies the possibility of very long time intervals of high network utilisation (superior to the expected mean), simultaneous bursty traffics could suffer from huge delays or even high loss rates during these periods. To evaluate this phenomenon, also known as "starvation" [10], we propose the scheme depicted in figure 4. As it can be seen from the figure, two streams are multiplexed on the same ATM node. The first traffic (X_n) corresponds to a VBR video stream while the second (Y_n) consists in a bursty data source with lower priority than video. In particular, as data source we consider a 13 hour HTTP trace containing the traffic of more than 500 Web users*. The channel bandwidth or service rate is assigned to be equal to the peak rate of the video signal so that it is guaranteed that video service will experience neither delays nor losses. Oppositely, according to an ABR (Available Bit Rate) or UBR (Unspecified Bit Rate) policy, the data traffic will employ the remaining bandwidth that, for each GOP, video does not utilise. In case of congestion, video traffic has higher priority and, therefore, data traffic will be buffered in a queue. This scenario could correspond to a real ATM transmission in which ABR and UBR services try to optimise the available bandwidth that other streams underutilise. For this reason traffic is measured in terms of ATM cells, considering a payload of 48 bytes for each cell.

To analyse the impact of long range dependent video traffic on the multiplexing performance, we propose to compare the QoS of data traffic when using the real MPEG trace as a video source, as well as when the real trace is substituted by different models.

To prove the scheme we consider the MPEG-1 video trace from Wurzburg University, as its duration is closer to that of data traffic. As alternatives to the real trace we utilise the same models which were considered in the previous section.

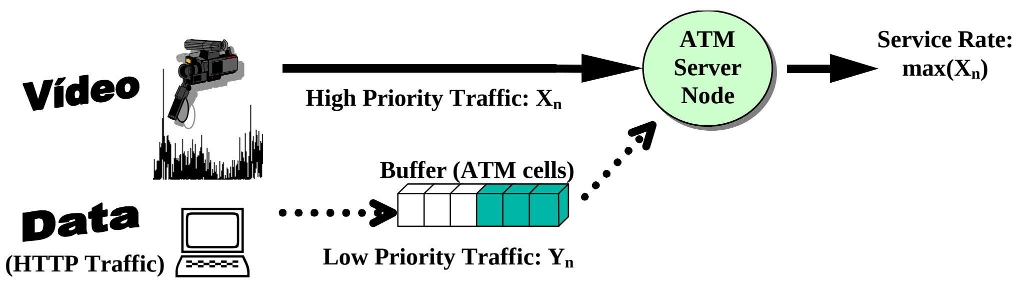


Figure 4. Proposed scheme for loss measurement of low priority traffic.

The results of the simulation are depicted in figure 5 which represents the cell loss rate that data traffic suffers when it is alternatively multiplexed on the link together with the different models and the real trace. In a real scenario HTTP data losses would provoke packet retransmissions which increment the delay and degrade the network throughput. The losses are calculated considering different realistic buffer sizes (for a service as HTTP, which is more delay-tolerant than video), ranging from 10 to 50000 cells. Figure 5 proves the importance of matching LRD, as just those models which capture it can accurately predict the impact of the starvation on low priority traffic. On the contrary, SRD and especially PDF models clearly underestimate queueing performance. This underestimation is more serious as the buffer size increases.

* The trace was captured on 4 March 1998 in a Ethernet LAN situated in the building of Alcatel ALSTHOM in Madrid (Spain).

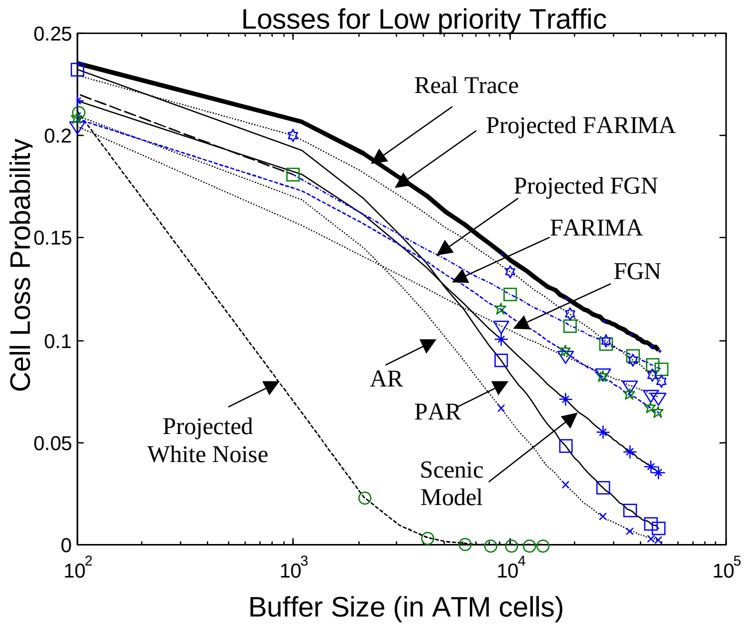


Figure 5. Losses for low priority traffic (HTTP flow)

5. CONCLUSIONS AND FUTURE WORK

In this work we have classified all the existing VBR video traffic models into three groups, depending on the statistical characteristics that they match. By using real MPEG traces we have compared the queuing performance of several types of models proving that under realistic conditions (low losses, small buffers) first order statistics, which are included in the PDF, are the most relevant characteristics to match, while SRD has a secondary importance and LRD or self-similarity could be neglected. However, although LRD can have no consequences for video service itself, it provokes long term variations of the available bandwidth in such a way that an ABR or UBR service could undergo higher loss rates than those predicted by SRD or PDF models. This phenomenon gives, for modelling purposes, a new importance to the existence of LRD or self-similarity within VBR video traffic.

In any case, the research on traffic management procedures (such as CAC, UPC, shaping,...) could benefit from this model classification as it is proved that the election of a proper modelling strategy basically depends on the time scale and the transmission scenario where the procedure will perform.

On the other hand, in this work we have just analysed the impact that visual signal has on traffic. However, at lower time scales, the influence of the encoding scheme should be taken into account. In the case of MPEG, the fixed GOP format determines an asymmetrical distribution of the short-term traffic load. This cyclical asymmetry imposes on the video signal a strong non- stationarity which must be characterised by an specific model.

As a future work, we propose to investigate the actual impact of LRD properties by injecting as a background traffic a fractal or LRD flow in a real local area network. So, it would be possible to analyse the possible degradation of subjective quality that network users could perceive.

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