# Video Traffic Models Performance for Restricted and Non-Restricted Scaling Characterization

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*Abstract*—**In this paper we examined the performance of the $M/G/\infty$ and fBm models to represent video traffic with different time-dependence or scaling degrees. The queueing behavior was also investigated when fed by these models. Several encoded video sequences were used for the experiments to validate the models performance results.**

## I. INTRODUCTION

VIDEO traffic has an inherent time dependence scaling invariance due to its encoding process. Time-dependence impact on queueing performance is still a very interesting research challenge. Recent studies based on asymptotics [1][2][3] queueing behavior showed that time-dependence has no significant impact on buffer/network performance. The main drawback of this research area concerns the lack of accurate traffic/network models. An accurate traffic model should represent the first and second-order statistics. Besides, it should be tractable in terms of queueing theory.

In this work we examined the queueing behavior fed by the restricted $M/G/\infty$ and the non-restricted fBm time-dependent traffic models. The models performance were evaluated in terms of video traffic time-dependence, tail-distribution and autocorrelation characterization. The models queueing performance were then examined in terms of their effective bandwidth (EB) results. We show that the heavy-tail distribution have more impact on queueing performance compared to the time-dependence characteristics, even for large buffer sizes.

The rest of the paper is organized as follows. In Section II we present a brief overview of $M/G/\infty$ and fBm models. Section III describes the effective bandwidth concepts. In Section IV the main results are presented and discussed. Finally, Section V is devoted to the conclusions of this work.

## II. THE $M/G/\infty$ AND FBM INPUT PROCESSES

In our analysis we considered the $M/G/\infty$ point process and fBm models to represent the time-dependence of scaling traffic characteristics. By definition the $M/G/\infty$ represents the time dependence degree ($H \geq 0.5$) for only a restricted period of time. However, this restricted time could be enough to investigate the impact of the traffic dependence on performance measures. The fBm is a non-restricted time dependence model since it can represent the whole scaling degree range ($0 < H < 1$). A stochastic process can be classified by its dependence degrees: Long-Range dependent (LRD) ($H > 0.5$), Short-Range dependent (SRD) ($H = 0.5$) or Anti-persistent ($H < 0.5$). .

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### A. $M/G/\infty$

For the $M/G/\infty$ process [4] the input/source is considered an infinite server with $G$ distribution service time fed by a Poisson process with $\lambda$ mean arrival rate, i.e., the input process is defined by the $\lambda$ rate and $G$ distribution. The $M/G/\infty$ generated process has an autocorrelation function (ACF) defined by

$$\rho(k) = e^{-\beta\sqrt{k}}, \qquad k = 0, 1, 2, ... \qquad . \tag{1}$$

This ACF shall lead to a restricted time-dependence degree representation or duration. The $\beta$ parameter is obtained from the video traces to fit sequences ACF. The $G$ distribution is related to the ACF by the expression

$$P[\sigma = k] = \frac{\rho(k-1) - 2\rho(k) + \rho(k+1)}{1 - \rho(1)} \tag{2}$$

where $\rho(k)$ is a decreasing and integer-convex function with $\rho(0) = 1 > \rho(1)$ and $\lim_{k\to\infty}\rho(k) = 0$. The $G$ distribution is obtained by using (1) into (2).

To fit the real traffic distribution a hybrid Poisson to Gamma/Pareto transformation (PGP) is performed keeping the ACF obtained from video traces.

### B. fBm

The fractional Brownian motion (fBm) is a gaussian stochastic process ($X_H(t)$) indexed in $\Re$ with zero mean and continuous sample path (null at origin). The variance of its independent increments is proportional to its time interval accordingly to the expression

$$Var[X(t_2) - X(t_1)] \propto |t_2 - t_1|^{2H}, \tag{3}$$

for $0 \leq t_1 \leq t_2$. It can be proven [5] that the fBm is a stationary and self-similar process with parameter $H$, i.e., its statistical characterization holds for any time scale. Thus, for any $\tau$ and $r > 0$, we have

$$[X_H(t+\tau) - X_H(t)]_{\tau\leq 0} \overset{d}{\approx} r^{-H}[X_H(t+r\tau) - X_H(t)]_{\tau\leq 0} \tag{4}$$

where $r$ is the process scaling factor. Because $X_H(t)$ is gaussian, it is completely characterized by its mean (null) and its covariance function, which is given by

$$\rho(k) = \frac{1}{2}\sigma^2[(k+1)^{2H} - 2k^{2H} + (k-1)^{2H}]. \tag{5}$$

Norros [8] proposed a discretization procedure of a fBm process to represent a traffic stream with scaling characteristics. Denoting $A(t)$ the number of received packets/cells by a multiplexer up to time $t$, we have

$$A(t) = mt + \sqrt{am} X_H(t), \quad (6)$$

where $m$ is the mean rate of the arrival process and $a = \frac{Var[A(t)]}{(mt)^{2H}}$ is a variance coefficient. We considered A(t) as one of the arrival process representing a video connection.

For the simulation experiments the fBm sample paths were generated by the well known *Random Midpoint Displacement* [10] algorithm. The fBm samples generation depends only on $m$, $\sigma$ and $H$ parameters. However, the $M/G/\infty$ $G$ distribution fitting procedure leads to a complex sample generation.

## III. Effective Bandwidth Concepts

The models performance were also examined in terms of their effective bandwidth results. For the analysis we considered the values obtained from the Norros equation [8] and simulation experiments. For a detailed description of EB definitions and formulations the reader should refer to [11].

Consider $A(t)$ as a fBm traffic process, defined in (6) with parameters $m$, $a$ and $H$; a queue system with deterministic service $C$ and an infinite buffer $Q$. The buffer occupation is the stochastic process $Q(t)$ defined as

$$Q(t) = \sup_{s \le t} (A(t) - A(s) - (t-s)C), \; t \in (-\infty, \infty). \quad (7)$$

If $\epsilon = P(Q > B)$ is the probability that a buffer of size $Q$ becomes larger than a limit $B$, the required $C_A(n)$ for an aggregate flow of $n$ connections is defined as

$$C_A(n) = nm + (\kappa(H)\sqrt{-2\ln\epsilon})^{\frac{1}{2H}} B^{\frac{H-1}{H}} (nma)^{\frac{1}{2H}}, \quad (8)$$

where $\kappa(H) = H^H(1-H)^{1-H}$.

To evaluate the EB from (8), we determine the maximum number of connections ($n_{max}$) which can be admitted in a link with capacity $C$ by

$$n_{max}m + (\kappa(H)\sqrt{-2\ln\epsilon})^{\frac{1}{2H}} B^{\frac{H-1}{H}} (n_{max}ma)^{\frac{1}{2H}} \le C. \quad (9)$$

Hence, the effective bandwidth of each video traffic connection can be evaluated by

$$B_e = \frac{C}{n_{max}} \quad (10)$$

## IV. Results and Discussions

Following in this section, we present the performance results for the $M/G/\infty$ and fBm models. The obtained ACF, tail distribution and EB curves are showed for both models and for different video traffic sequences.

### A. Analysis Environment

We considered five encoded video sequences: *Star Wars*, *Silence of the Lambs* (H.263), *Race* (MPEG-4) and *Mr. Bean* (MPEG-1)[1]. The *TTennis02* ($H = 0.2$) sequence was examined in order to evaluate the models ability to deal with anti-persistent ($H < 0.5$) traffic. This sequence was generated by the fBm process (eq. (6)) considering the $m$ and $\sigma$ parameters obtained from the real standard MPEG-2 *Table-Tennis*.

Table 1 presents the sampling rate $sr$, the mean $m$, the standard deviation $\sigma$ and the estimated Hurst $\hat{H}$[2]

TABLE I
VIDEO SEQUENCES PARAMETERS.

| Sequence | $sr$ (frames/sec) | $m$ (kbps) | $\sigma$ (kbps) | $\hat{H}$ |
|---|---|---|---|---|
| *Star Wars* | 24 | 5335.8 | 1200.8 | 0.830 |
| *Silence* | 25 | 891.6 | 344.09 | 0.822 |
| *Bean* | 25 | 183.92 | 179.0 | 0.817 |
| *Race* | 25 | 1804.8 | 537.79 | 0.870 |
| *TTennis02* | 50 | 10176 | 2049.9 | 0.260 |

To fit a monotone convex ACF the MPEG *Race* and *Bean* sequences were smoothed within the GoP level such that

$$X_m^{GoP} = \sum_{n=12(m-1)+1}^{12m} X_n \qquad m = 1, ..., N/12 \quad (11)$$

where $X_n$ is the number of bytes per frame ($n = 1, ..., N$) and $N$ is the sequence size (in frames) of the original trace. The parameters of the new smoothed sequences are given in Table II. As we note, due to ACF smoothing procedure the sequences present a changing in the $\sigma$ value leading to different $\hat{H}$ parameters.

TABLE II
GOP SEQUENCES PARAMETERS.

| Sequence | $m$ (kbits/sec) | $\sigma$ (kbits/sec) | $\hat{H}$ |
|---|---|---|---|
| $Bean^{GoP}$ | 183.9 | 92.34 | 0.902 |
| $Race^{GoP}$ | 1804.8 | 308.54 | 0.840 |

Tables III and IV show the new parameters estimated from the samples generated by the $M/G/\infty$ and fBm models considering the smoothing procedure (see eq. (11)).

TABLE III
$M/G/\infty$ SEQUENCES PARAMETERS.

| Sequence | $m$ (kbits/sec) | $\sigma$ (kbits/sec) | $\hat{H}$ |
|---|---|---|---|
| *Star Wars*$_{M/G/\infty}$ | 5508.4 | 1261.7 | 0.892 |
| *Silence*$_{M/G/\infty}$ | 951.8 | 298.66 | 0.812 |
| *Bean*$^{GoP}_{M/G/\infty}$ | 211.67 | 120.30 | 0.840 |
| *Race*$^{GoP}_{M/G/\infty}$ | 1890.3 | 308.54 | 0.822 |
| *Tennis02*$_{M/G/\infty}$ | 10960.4 | 1892.6 | 0.644 |

### B. ACF Results

Figure 1 depicts the ACF curves obtained from the original traces and for the $M/G/\infty$ and fBm models. As expected the

[1]The *Star Wars* sequence is available at ftp://ftp.research.telcordia.com/pub/vbr.video.trace/.
The *Silence of the Lambs* and *Mr. Bean* sequences are available at http://www-tkn.ee.tu-berlin.de/ fitzek/TRACE/ltvt.html. The *Race* sequence is available at http://nero.informatik.uni-wuerzburg.de/MPEG/traces/.

[2]For the Hurst estimation parameters we use use the R/S [6] and Wavelet (Abry-Veitch)[7] estimators[3]. The estimation results were quite similar for all sequences and for both methods.

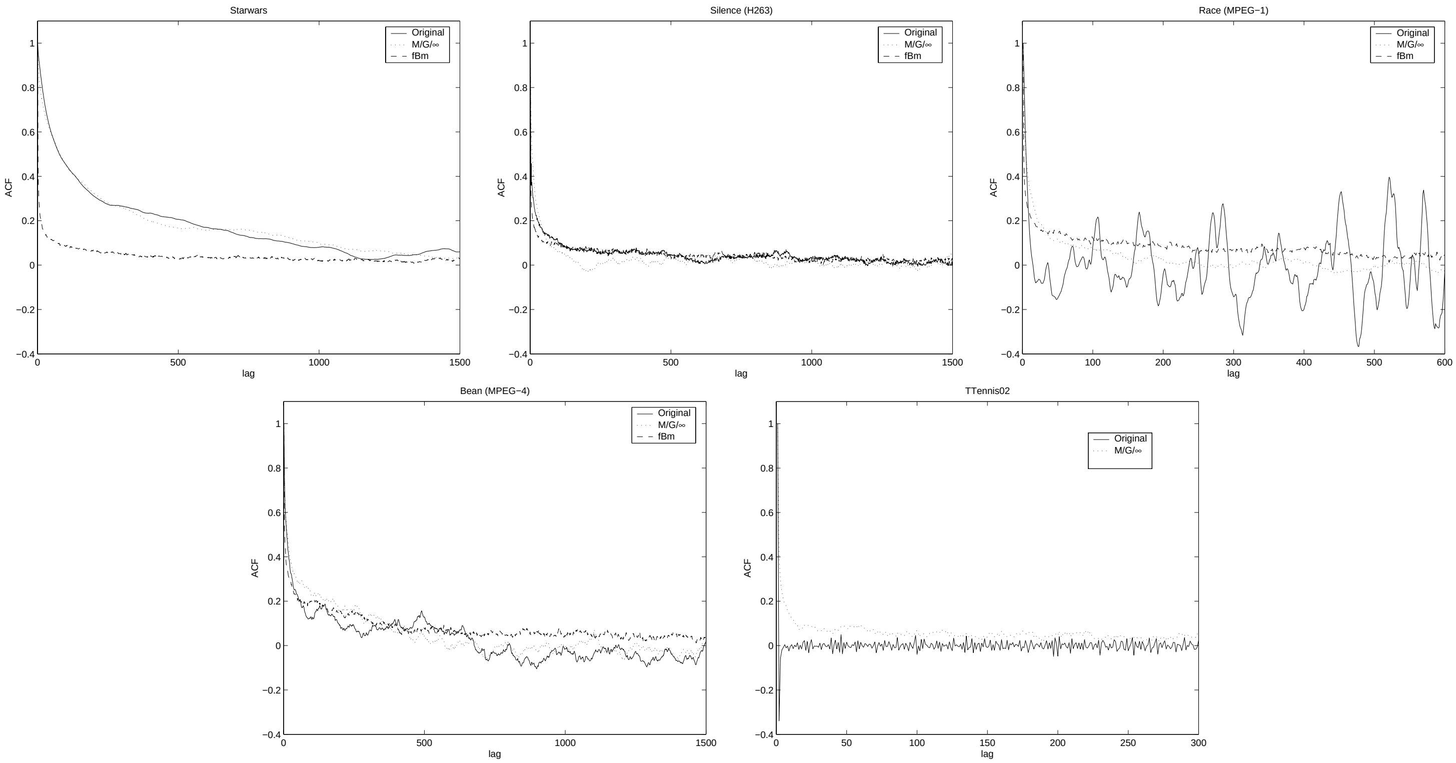


Fig. 1. ACF for (a) Star Wars, (b) Silence, (c) Race, (d) Bean and (e) TTennis02 sequences.

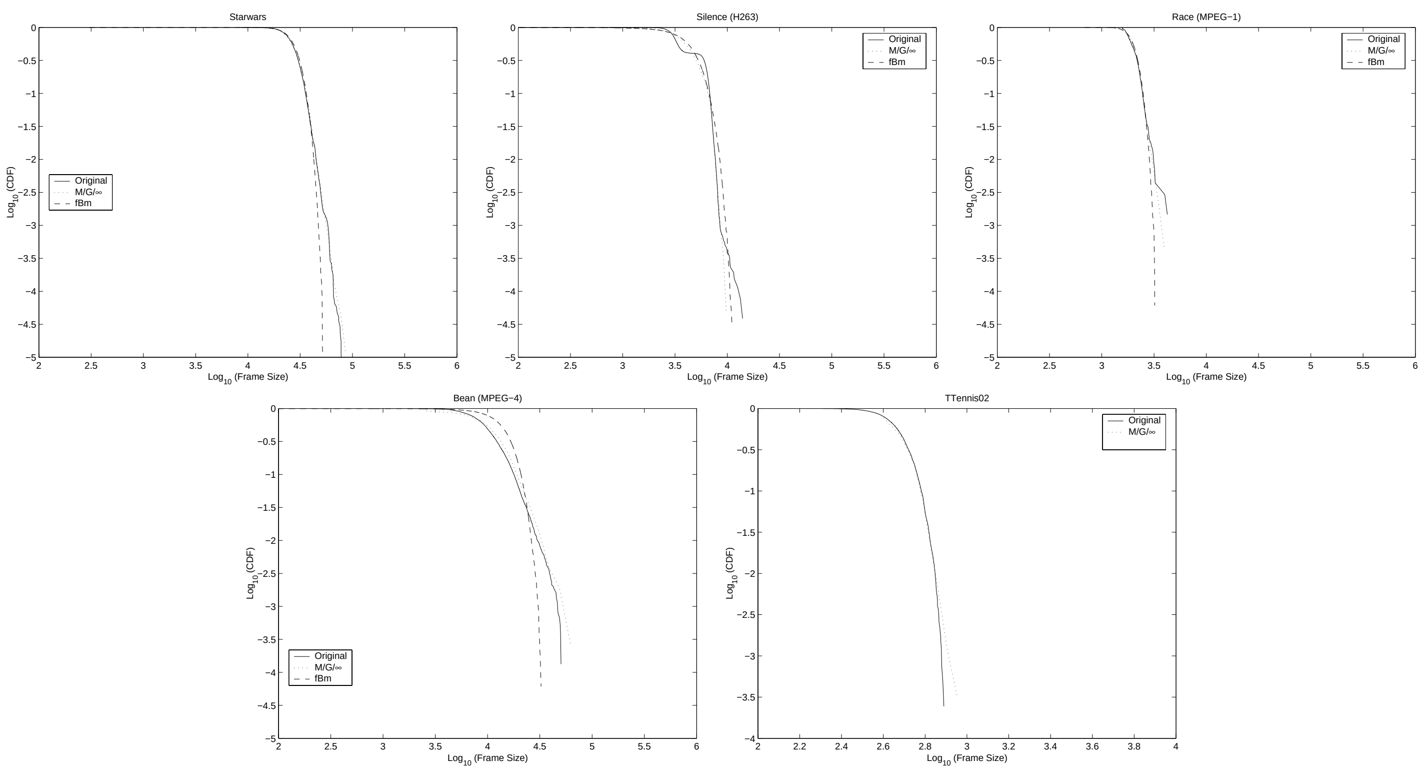


Fig. 2. HTD for (a) Star Wars, (b) Silence, (c) Race, (d) Bean and (e) TTennis02 sequences.

$M/G/\infty$ presented better fitting results compared to the fBm for the video sequences with subexponential ACF (*StarWars*). This was not the case for the *Race* and *TTennis02* sequences. The best ACF fitting results were obtained for the *Silence* sequence for both models.

### C. Heavy-Tail Distribution Results

A random variable $X$ has a heavy tail distribution (HTD) if

$$P(X > x) \cong cx^{-\alpha}, \qquad x \to \infty. \tag{12}$$

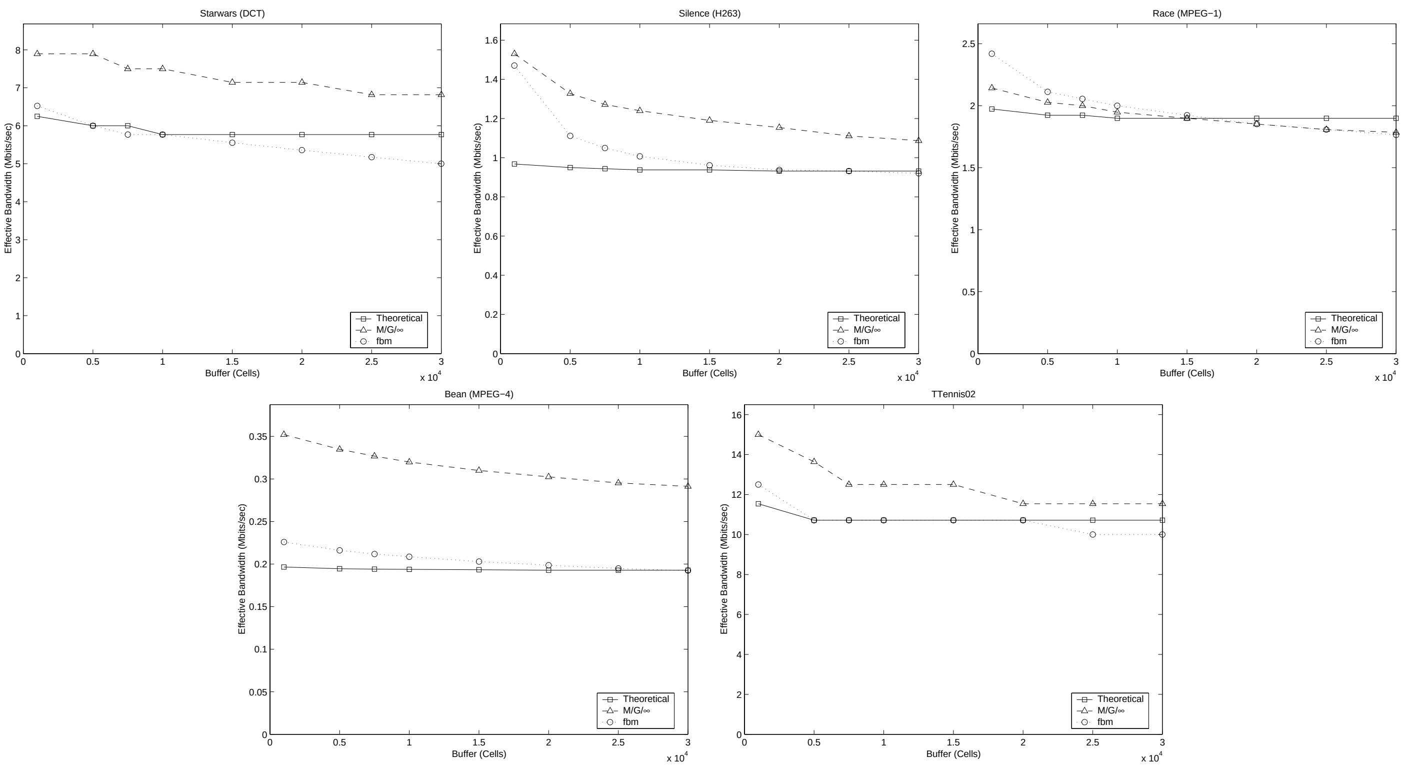


Fig. 3. Effective Bandwidth for (a) Star Wars, (b) Silence, (c) Race, (d) Bean and (e) TTennis02 sequences.

TABLE IV

fBM SEQUENCES PARAMETERS.

| Sequence | $m$ (kbits/sec) | $\sigma$ (kbits/sec) | $\hat{H}$ |
|---|---|---|---|
| *Star Wars*$_{fBm}$ | 5426.6 | 1192.1 | 0.819 |
| *Silence*$_{fBm}$ | 896.8 | 340.59 | 0.837 |
| *Bean*$_{fBm}^{GoP}$ | 235.5 | 87.734 | 0.882 |
| *Race*$_{fBm}^{GoP}$ | 1808.2 | 303.18 | 0.852 |

where $0 < \alpha < 2$ is the shape parameter and $c$ is a positive constant[9]. The Pareto distribution is one of the most important HTD since it well fits the LRD characteristics.

The HTD results for all sequences are depicted in Figure 2. As we observe the $M/G/\infty$ and fBm tail distribution were very close for the *Race* sequence.

For the *Bean* sequence however the fBm HTD were quite different from original trace. The $M/G/\infty$ was not able to capture the real *TTennis02* HTD since it is by definition better for gamma/pareto tails representation.

### *D. Effective Bandwidth Results*

The EB simulation results for both models were compared to the theoretical values obtained for Norros equation (8). For the experiments we considered large buffer sizes ($B \geq 1000$ cells, 1 cell=424 bits), link capacity $C = 150$ Mbps and $\epsilon = 10^{-4}$. The EB results are presented on Figure 3.

We can note from the *Silence* sequence that despites the similar ACF (see Figure 1) obtained from both models, the EB $M/G/\infty$ values were largely different from the fBm model. This is explained by the different HTD results (see Figure 2). For the *Race* sequence however, both models obtained close EB results compared to the theoretical values. This is due to the fact that *Race* is a gaussian-like sequence. Moreover, both models obtained better HTD fitting results for this sequence. From the above discussion we should then conclude that the tail distribution is extremely relevant for the EB performance and shall be considered for buffer dimensioning and network design.

## V. CONCLUSIONS

The performance of $M/G/\infty$ and fBm models to represent the ACF, time-dependence or scaling degree and heavy-tail distribution was examined on this paper. In general the $M/G/\infty$ presented higher effective bandwidth values compared to the fBm model. The results also showed that the heavy-tail distribution has more impact on bandwidth than the dependence or scaling characteristics. Other heavy-tail distribution $M/G/\infty$ transformation, e.g., Poisson to Weibull or subexponential, shall be investigated to represent a wide-range of video sequences.

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