The Importance of Long-Range Dependence of VBR Video Traffic in ATM Traffic Engineering: Myths and Realities

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Background

1. VBR video traffic exhibits long-range dependence (LRD).

2. Wide interest & general concern.

3. Debate on the relevance of LRD.

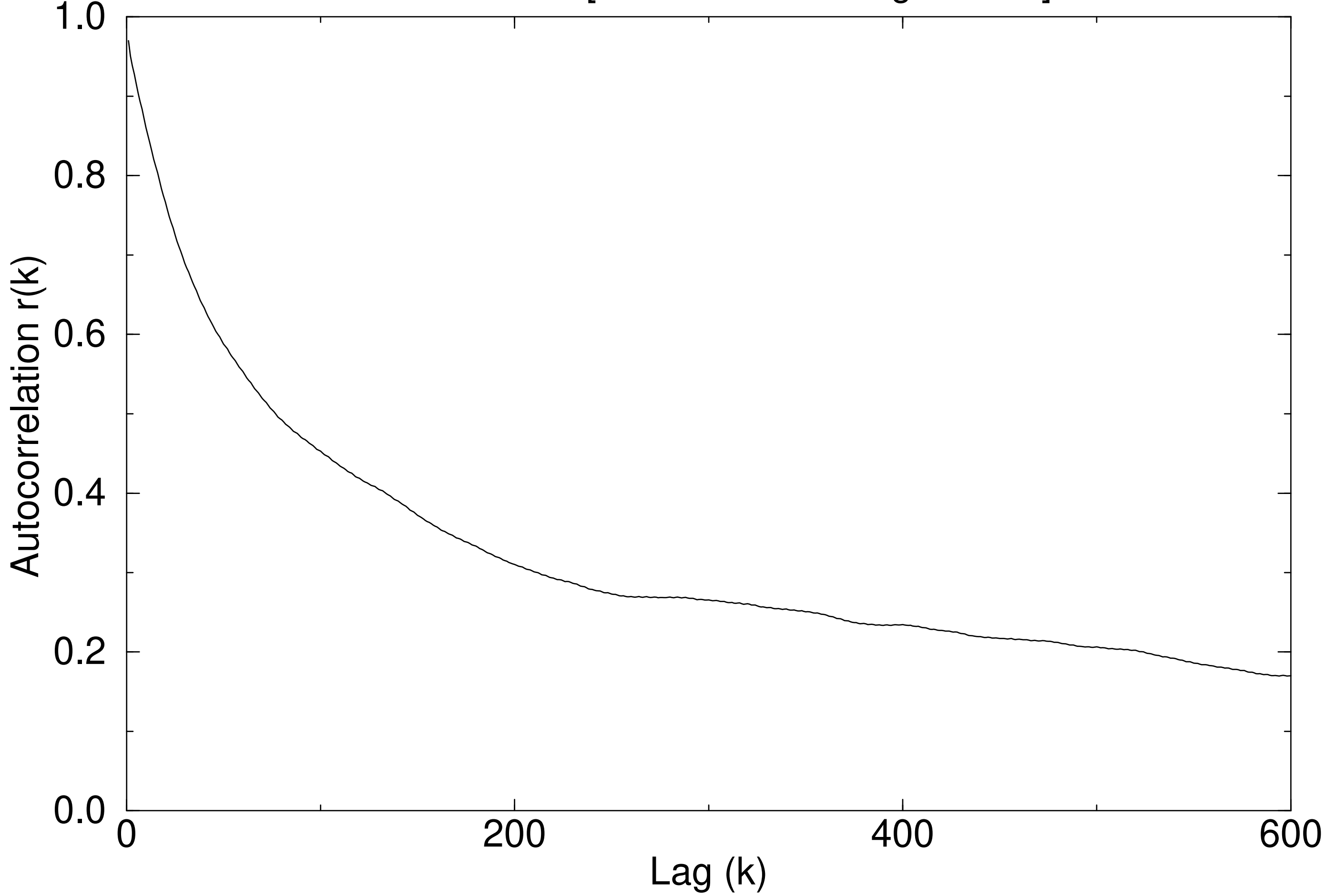
   - "Fatter-than-exponential" tail of ATM buffer overflow probability.

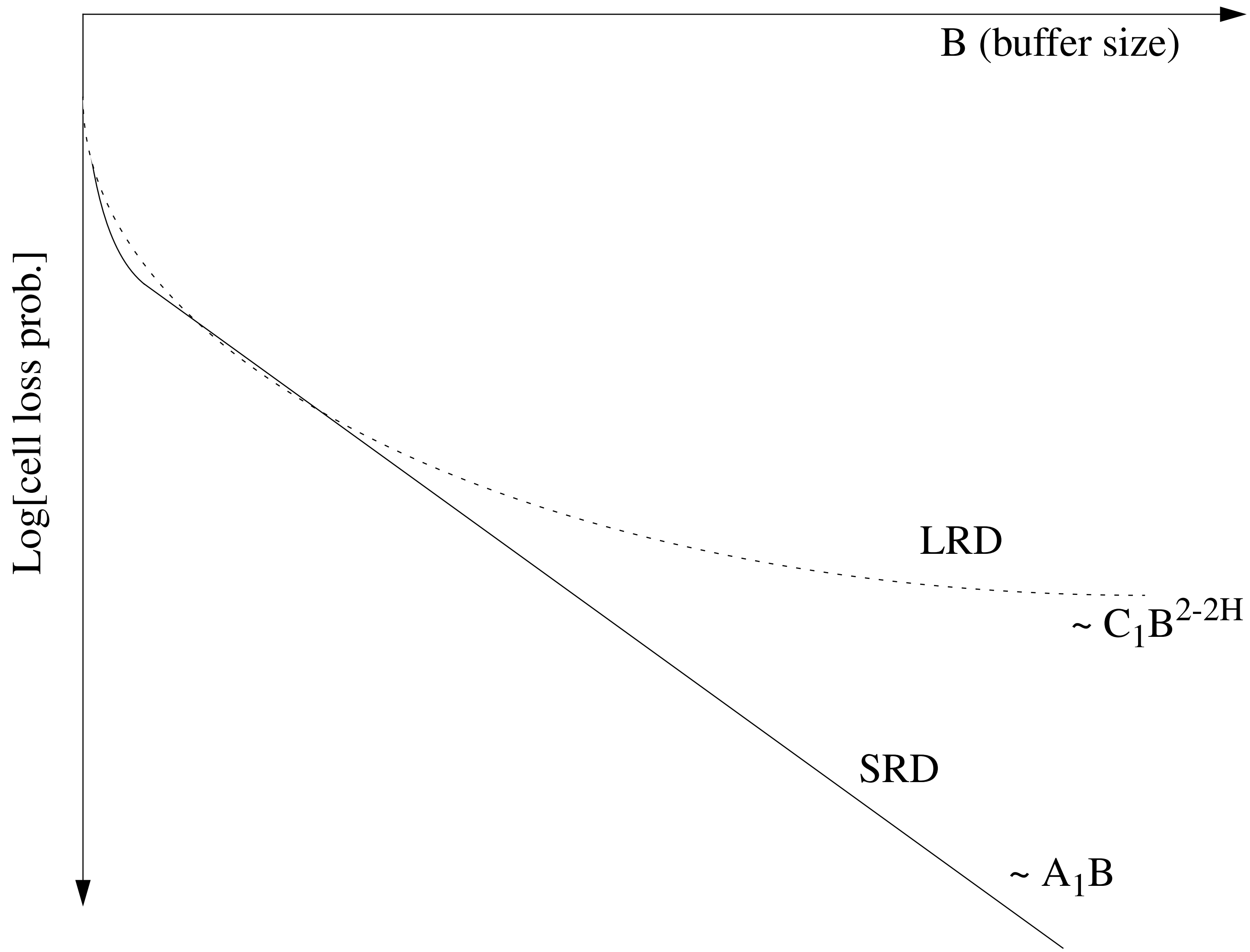
   - Prior work on video modeling with simple Markovian model produces good results.

   [Elwalid, Heyman, Lakshman, Mitra, and Weiss; IEEE JSAC, Aug. 1995]

Star Wars Movie

Hurst =~ 0.8 [Garrett and Willinger 1994]




B (buffer size)
Log[cell loss prob.]
LRD
~ C_1B^{2-2H}
SRD
~ A_1B

Outline

How important is LRD of real-time video applications in ATM traffic engineering?

Buffer Size (max delay): < 20 ~ 30 msec

Cell Loss Prob. (P_{Loss}): < 10^{-6}

I: Effect of long-term and short-term correlations on P_{Loss}

II: Efficacy of Markov models in predicting P_{Loss}

III: Relevant range of dependence (critical time scale)

Note: (i) video model rather than trace

(ii) same marginal distribution of frame size (Gaussian)

Definitions

$X = \{X_1, X_2, \ldots\}$ WSS process with ACF $r(k)$.

- X is *asymptotic* LRD process if

$$r(k) \approx Ak^{-(2-2H)}, \quad (k \text{ large})$$

- H: Hurst parameter ($1/2 < H < 1$)

(Note: Short-term correlations are arbitrary)

- X is *exact* LRD if

$$r(k) = 1/2\ \delta^2(k^{2H}),\ k = 1, 2, \ldots$$

ex) Fractional Gaussian Noise, Fractal modulated Poisson processes

I. Effect of *short*- and *long*-term correlations on P_{Loss}

- Construct two *asymptotic* LRD processes Z^a & V^v by

$$Z^a, V^v = \mathrm{DAR}(1) + \mathrm{FMPP}$$

DAR(p): Discrete Auto-Regressive model with order p.

FMPP: Fractal Modulated Poisson Process

$$r_v(k) = r_z(k) = \frac{v}{v+1} \cdot a^k + \frac{1}{v+1} \cdot \frac{1}{2} \cdot \delta(k^{2H})$$

- Z^a: same long-term, varying short-term correlations.
- V^v: same short-term, varying long-term correlations.

DAR(p) Process

$$X_n = V_n X_{n - A_n} + (1 - V_n)\varepsilon_n$$

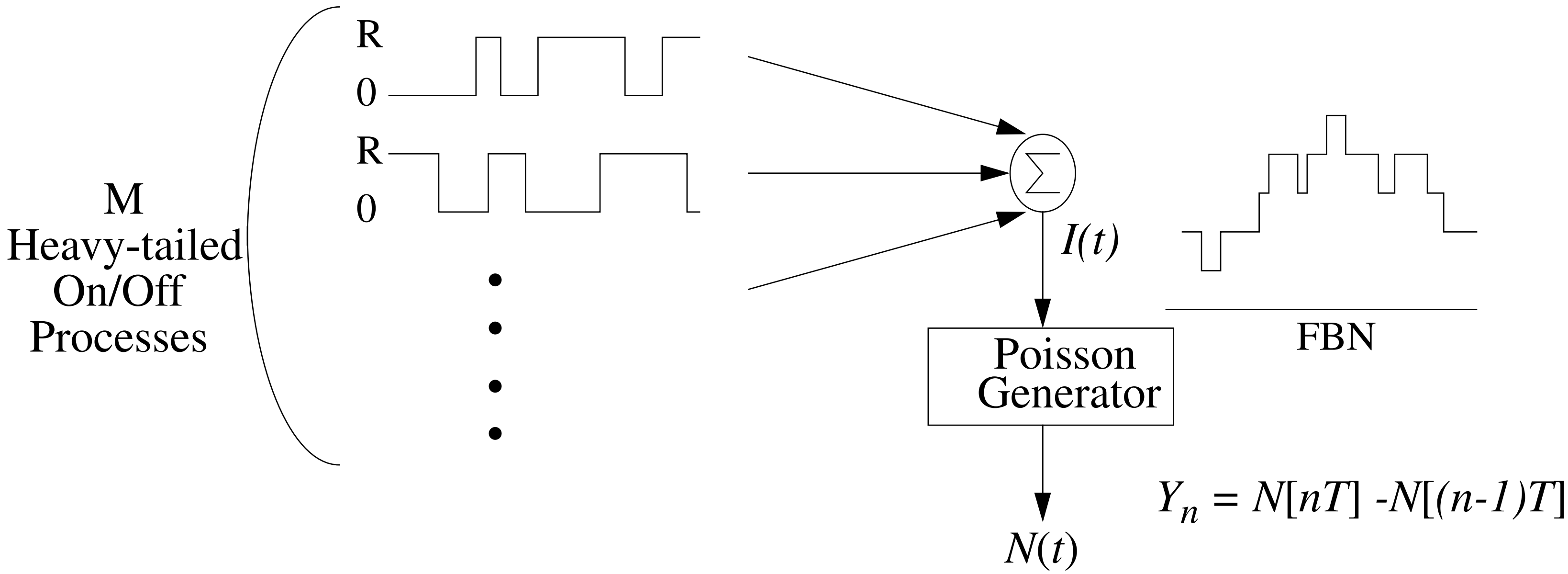
$\{\varepsilon_n\}$: i.i.d. R.V. with distribution π $(\varepsilon_n \in Z)$

$\{V_n\}$: Bernoulli R.V. $(V_n \in \{0,1\})$

$\{A_n\}$: i.i.d. R.V with $Pr(A_n = i) = a_i$, $i = 1, 2, \ldots, p$. $(A_n \in \{1, 2, \ldots, p\})$

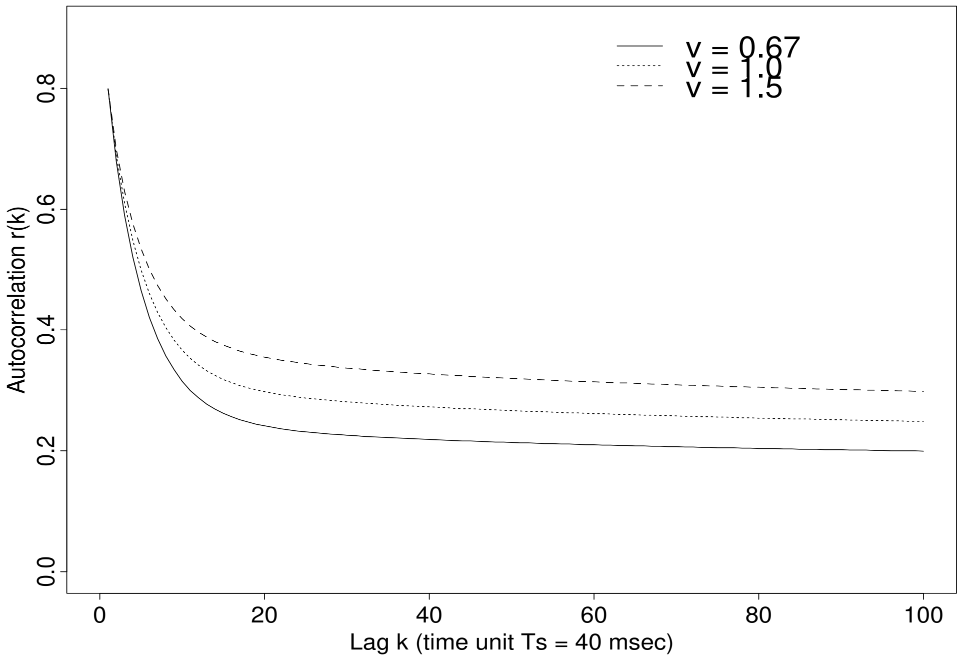
- $r_X(k) = \sum_{i=1}^{p} b_i z_i^{-k}$
- Correlations independent of marginal distribution π.
- Correlations matching up to p lags.
- Computationally efficient.

Fractal Modulated Poisson Process
(ex: FBNDP)

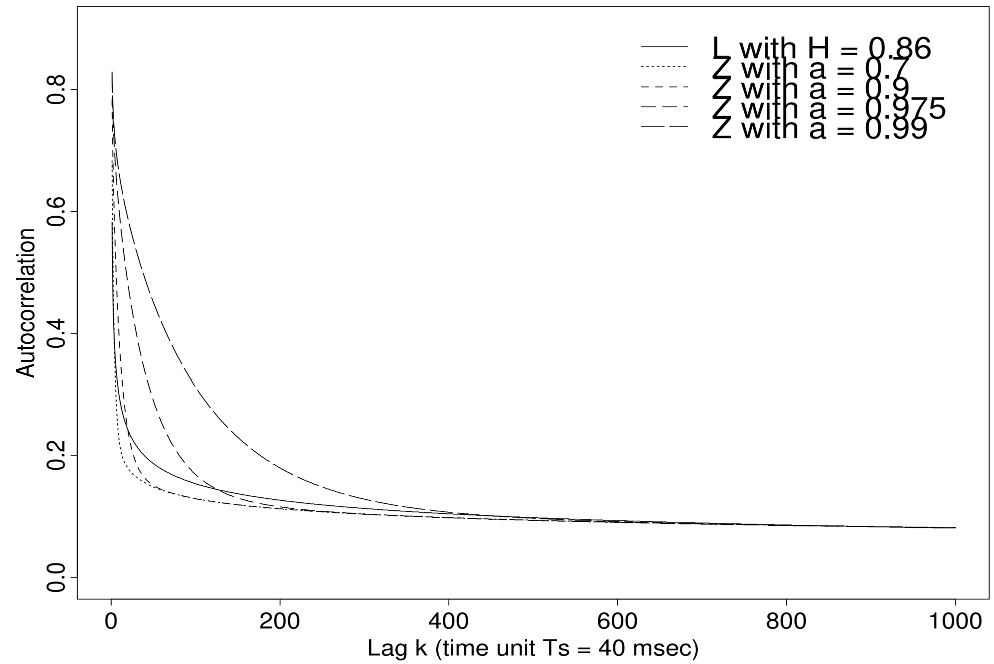


- Completely characterized by R, M, and pdf of on/off sojourn times.
- $r_Y(k) = \frac{1}{2}\delta^2(k^{2H})$, marginal distribution of $\{Y_n\}$ controlled by M.
- Computationally efficient

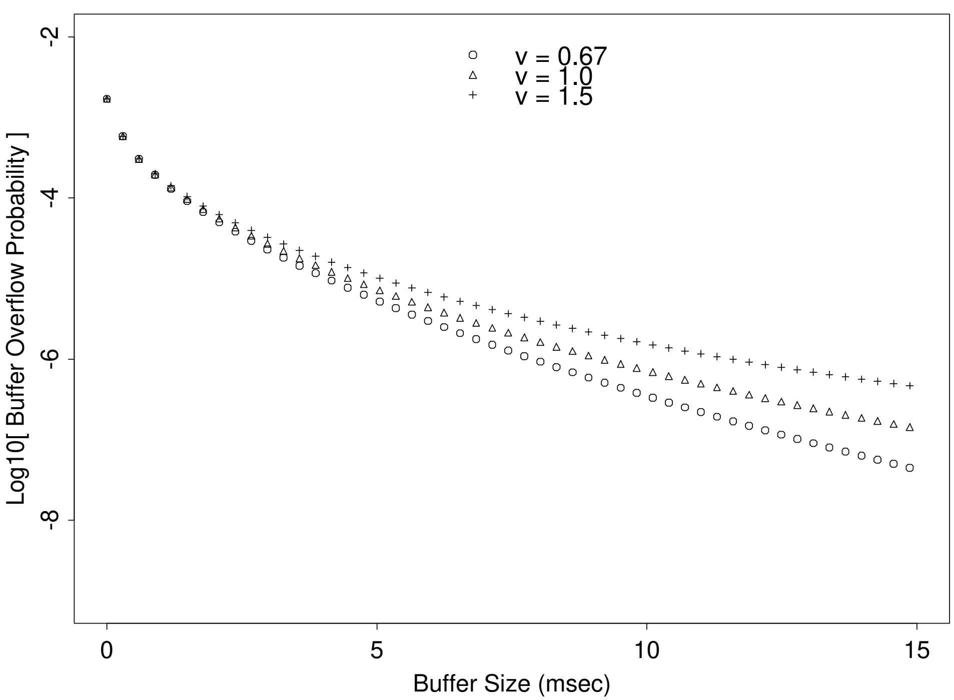
Varying Long-term Correlations (V^v)



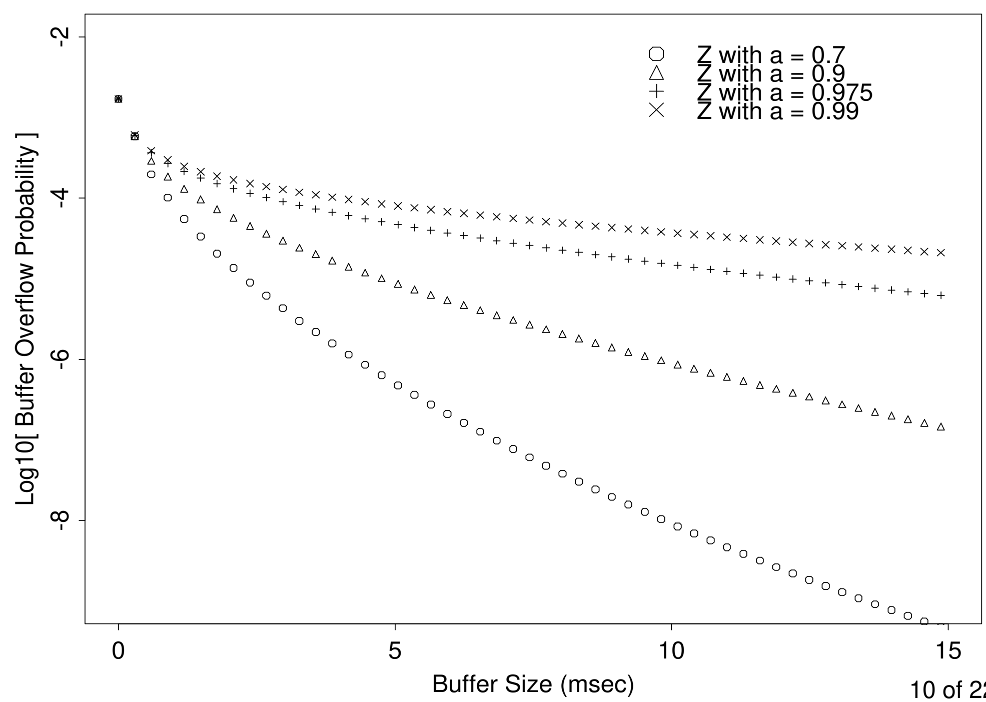
Varying Short-term Correlations (Z^a)



Effect on Cell Loss Prob.

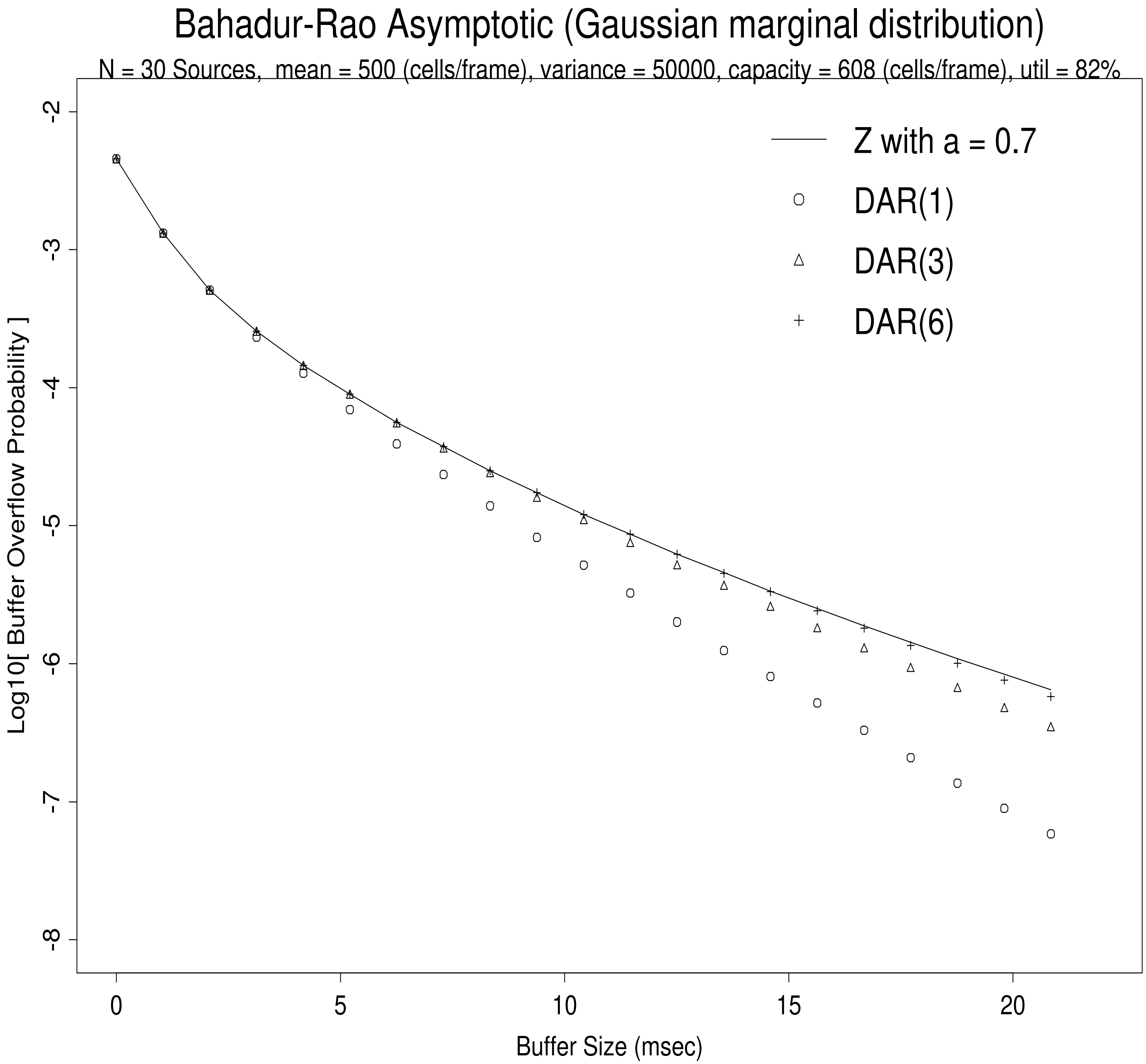


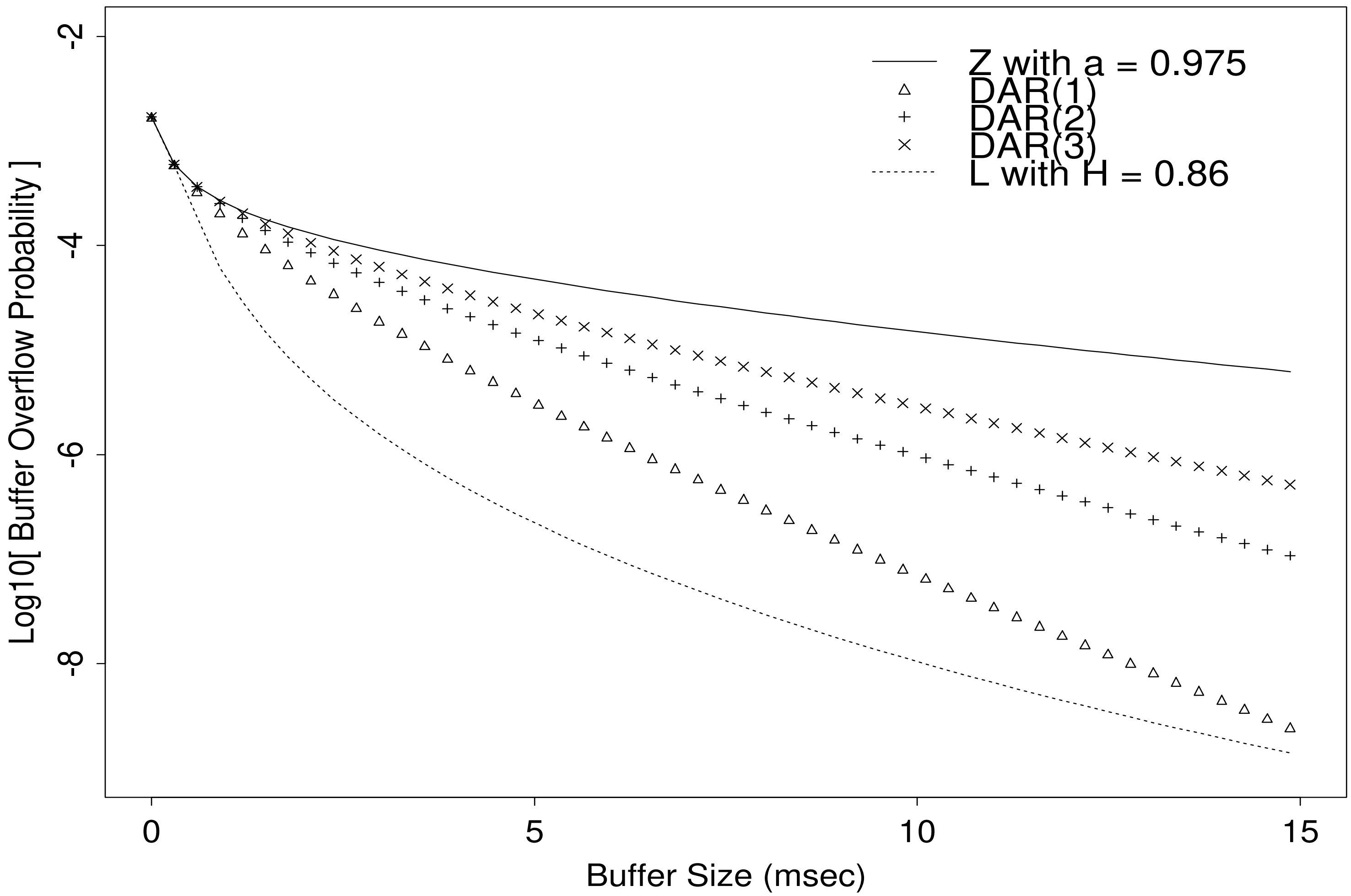
Effect on Cell Loss Prob.



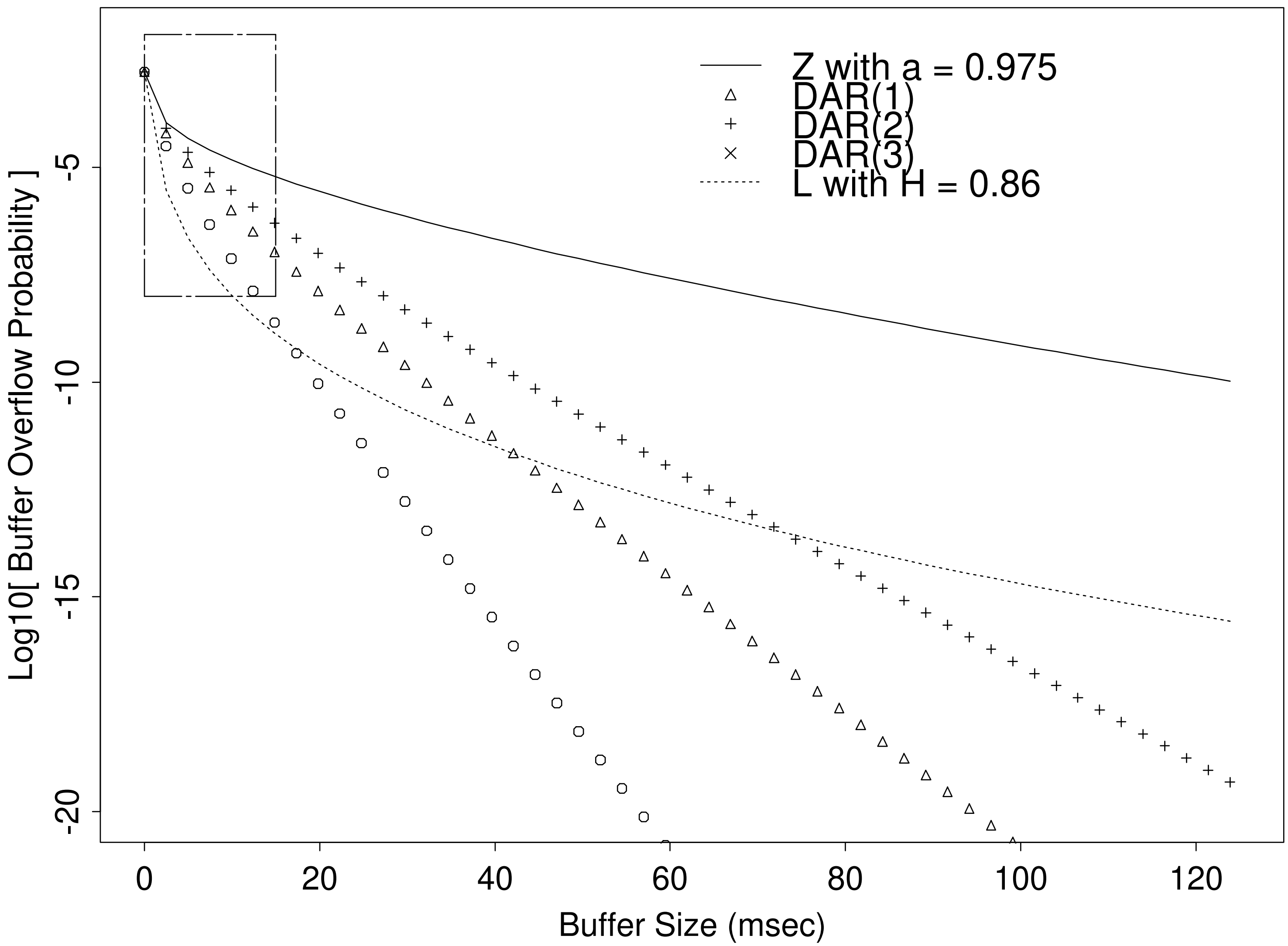
II. Efficacy of Markov models in predicting P_{Loss} of LRD traffic

- Target (asymptotic) LRD process Z^a
- DAR(p): matches the first p (p small) correlations
- Exact LRD model L based on FMPP: matches only the long-term correlations (Hurst parameter) of Z^a.
- Marginal distribution is same for all the models.


Bahadur-Rao Asymptotic (Gaussian marginal distribution)
N = 30 Sources, mean = 500 (cells/frame), variance = 50000, capacity = 608 (cells/frame), util = 82%
Z with a = 0.7
DAR(1)
DAR(3)
DAR(6)
Log10[Buffer Overflow Probability]
-2
-3
-4
-5
-6
-7
-8
0
5
10
15
20
Buffer Size (msec)



- L underestimating Z^a
- Larger p, better prediction



• L eventually outperforms DAR(p), but only over the range of no interest.

Analysis of Buffer Overflow Probability

[Courcoubetis & Weber, Duffield, De Veciana, etc.]

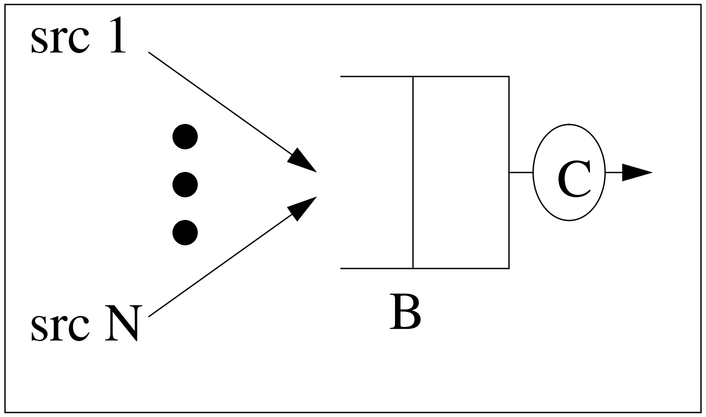
- For N Gaussian sources, each with mean μ, variance σ^2, and ACF r(k),

$$P(W > B) = \exp(-NI(c, b) + g(c, b, N))$$

$$\lim_{N \to \infty} g(c, b, N)/N = 0$$

$$I(c, b) \equiv \inf_{m \geq 1} \frac{[b + m(c - \mu)]^2}{2V(m)}$$

$$V(m) \equiv Var\left(\sum_{i=1}^{m} X_i\right) = \sigma^2\left[m + 2\sum_{i=1}^{m} (m - i) r(i)\right]$$



- b = amount of buffer space per source ($B = Nb$)
- c = amount of bandwidth per source ($C = Nc$)

Relevant Range of Dependence (Correlation):

Critical Time Scale (CTS)

- For given buffer size b and link capacity c,

$$m^*_b = \operatorname{arginf}_{m \geq 1} \frac{[b + m(c - \mu)]^2}{2V(m)} \text{ (in units of frame)}$$

☞ *Only the first (m^*_b-1) correlations are needed to evaluate P(W>B).*

☞ *Correlations beyond time scales ≥ m^*_b are irrelevant to P(W>B).*

☞ CTS $\equiv m^*_b$

Facts on CTS

- $m^*{}_0 = 1$

  $\Rightarrow$ No buffer, no effect of correlation on cell loss rate!

- $m^*{}_b < \infty$ as long as b < ∞.

- $m^*{}_b$ is linear with b for large b.

Related Work on CTS

- Frequency domain analysis [Li and Hwang]

  ⇒ *cutoff frequency.*

  ⇒ Low frequency behavior (long-term correlations) dominant impact on queueing performance. (???)

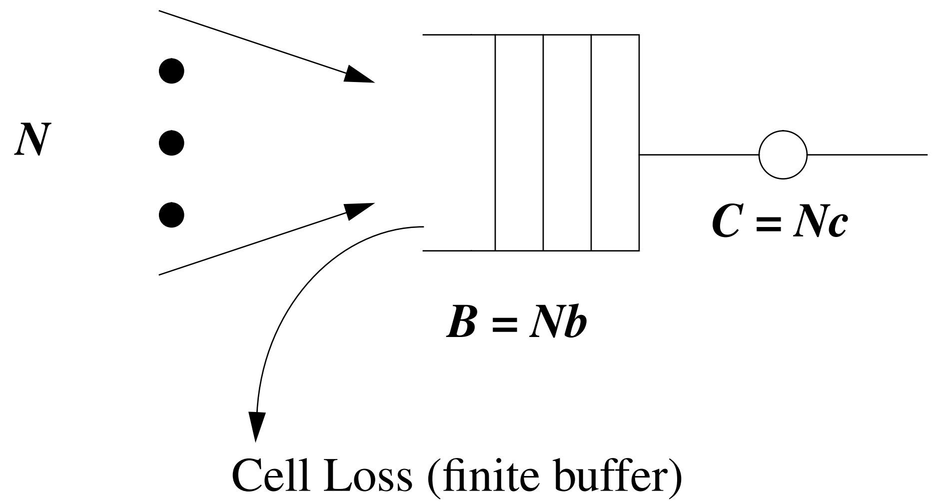
- Direct relation between *cutoff frequency* and *CTS*

  [Montgomery and DeVaciana].

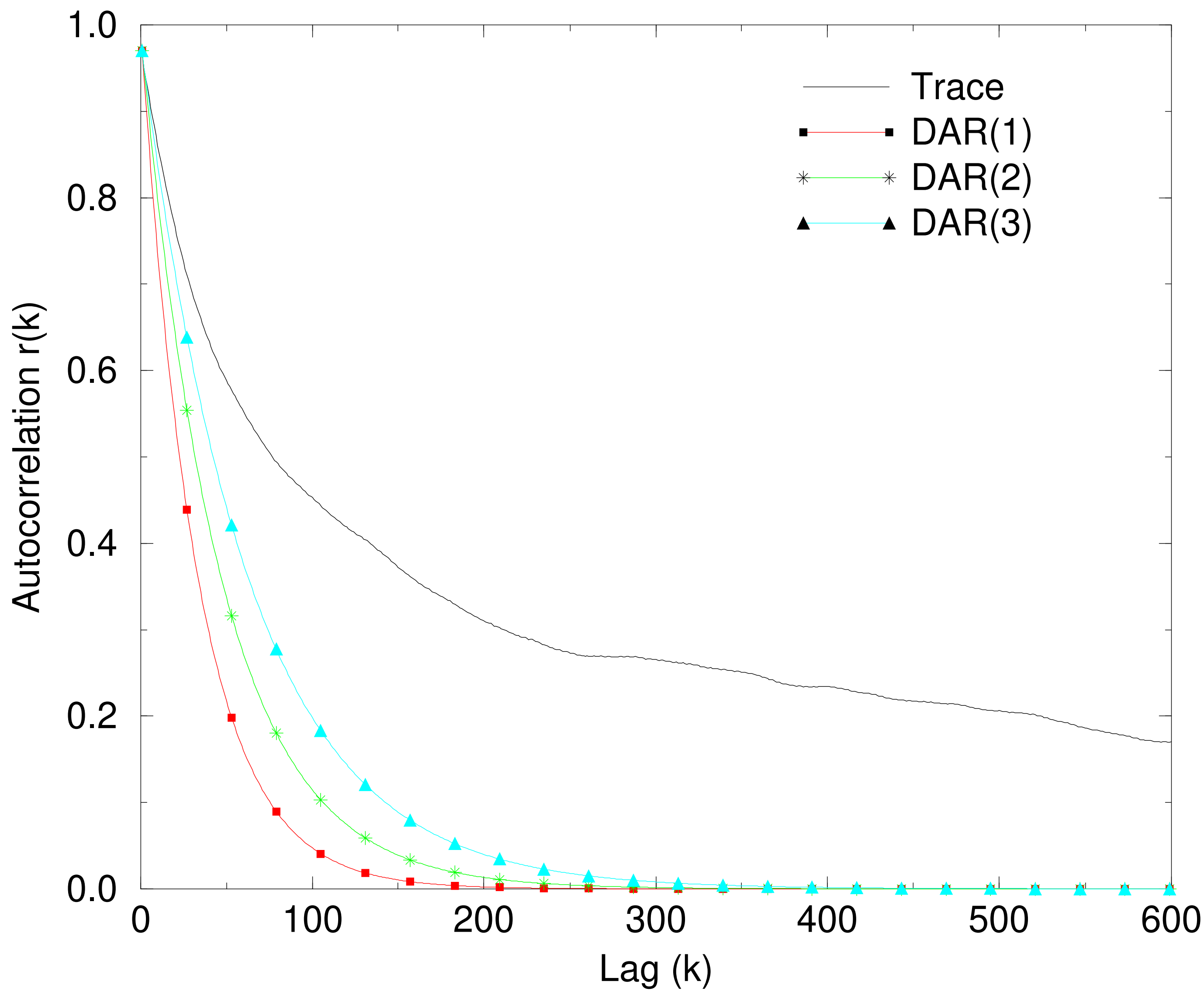
Simulation Study with Star Wars Movie

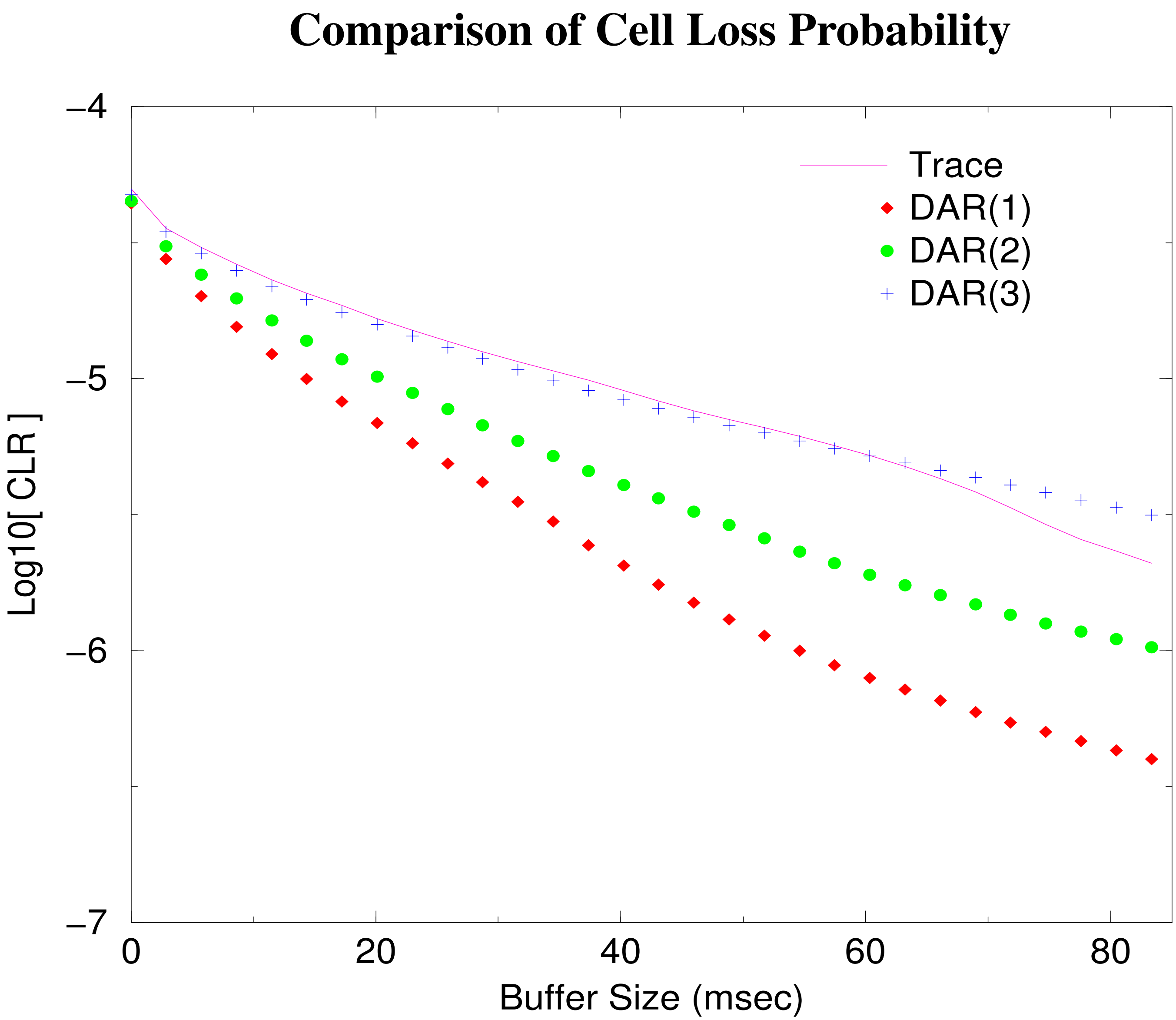
Simulation Setting:

Trace: Star Wars (intra-frame coding only) [Garrett 1993 PhD thesis]
Hurst parameter: about 0.8
cell size: 44 bytes/cell
mean rate = 632 cells/frame
min rate = 196 cells/frame
max rate = 1784 cells/frame
capacity = 725 cells/frame
link utilization = 0.89
number of sources = 20
cell loss curve of the trace averaged over 5 different sets of starting points
Empirical marginal distribution used for DAR(p), p = 1,2,3.
Length of each replication = 10,000 sec
number of replications per model = 60


N
C = Nc
B = Nb
Cell Loss (finite buffer)

Short-term Correlations Matching for Star Wars trace with DAR(p)




Comparison of Cell Loss Probability
Trace
DAR(1)
DAR(2)
DAR(3)
Log10[CLR]
Buffer Size (msec)
−4
−5
−6
−7
0
20
40
60
80