

Self Similar Traffic Modeling in Communication Networks

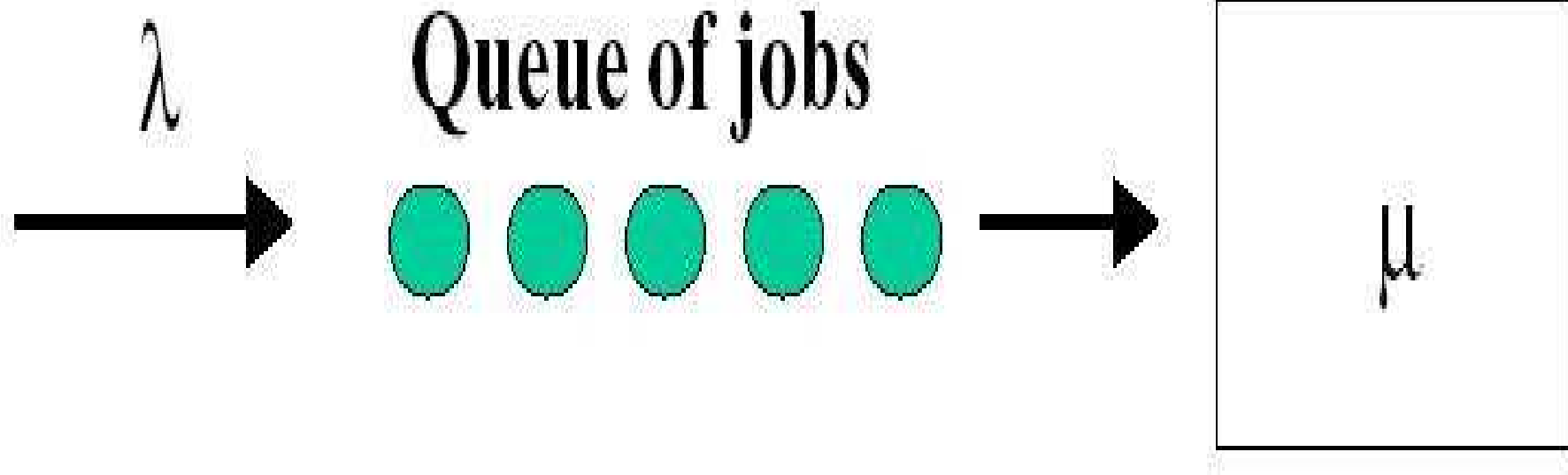
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Presentation Agenda

- Introduction
- Understanding Self-Similarity
- Effect of Self-Similarity on Network Performance
- Modeling Techniques
- Tools for Measurement
- My Work
- Conclusion
- References

Introduction : A simple queue



- λ = Arrival rate.
- μ^{-1} = Mean service time

Introduction : Background

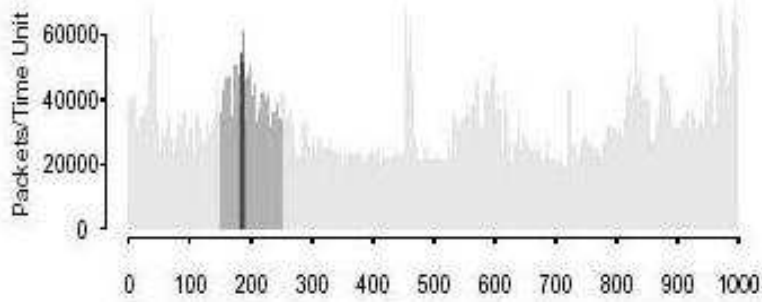
- Models of the traffic offered to a network critical to providing high QoS.....
- Traditionally, arrivals in network queues assumed to be Poisson.
- Empirical studies (Leland94) show that packet inter-arrivals clearly differ from exponential in WANs and LANs.
- Strong argument for divergence from Poisson processes shown in (Paxson95), (Crovella99).

Introduction (contd.)

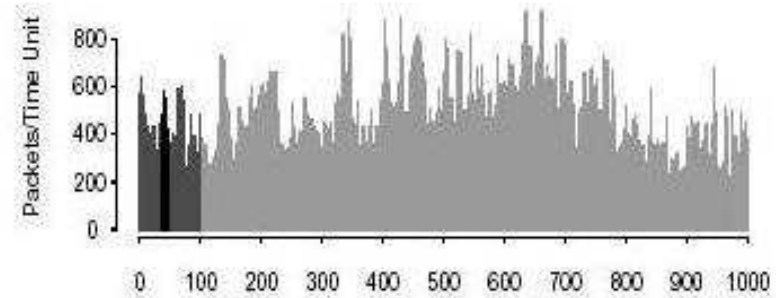
- Self-Similar Processes are theoretically much different from Poisson processes.
- Traffic *bursts* appear over wider range of time scales.
- Longer-term *spikes, ripples* and *swells*.
- Essentially self-similar processes exhibit *fractal-like* behavior.

Understanding Self-Similarity

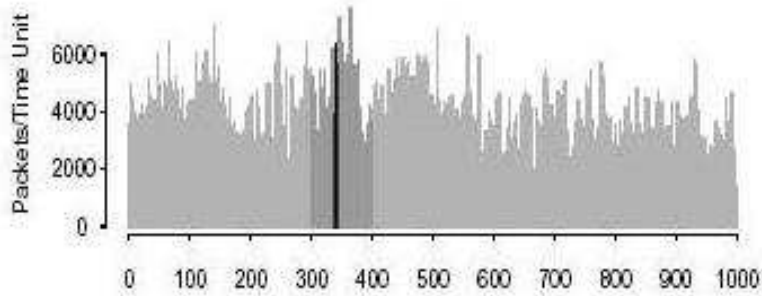
● Self-Similarity:



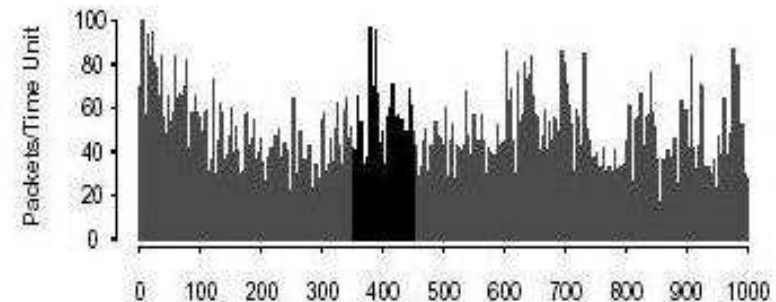
Time Units, Unit = 100 Seconds (a)



Time Units, Unit = 1 Second (c)



Time Units, Unit = 10 Seconds (b)



Time Units, Unit = 0.1 Second (d)

Packet traffic count exhibiting self-similarity (Leland94)

Understanding Self-Similarity (contd.)

- Mathematically, a continuous-time process, $Y = Y(t), t \geq 0$ is *self-similar* if it satisfies the condition:

$$(1) \quad Y(t) \stackrel{d}{=} a^{-H} Y(at), \forall t \geq 0, \forall a \geq 0, 0 \leq H \leq 1$$

, where equality is in terms of distribution. H is known as the Hurst parameter.

- From an engineering point of view, the distribution becomes heavy-tailed, i.e.

$$(2) \quad P[X \geq x] \sim x^{-\alpha}, x \rightarrow \infty, 0 \leq \alpha \leq 2.$$

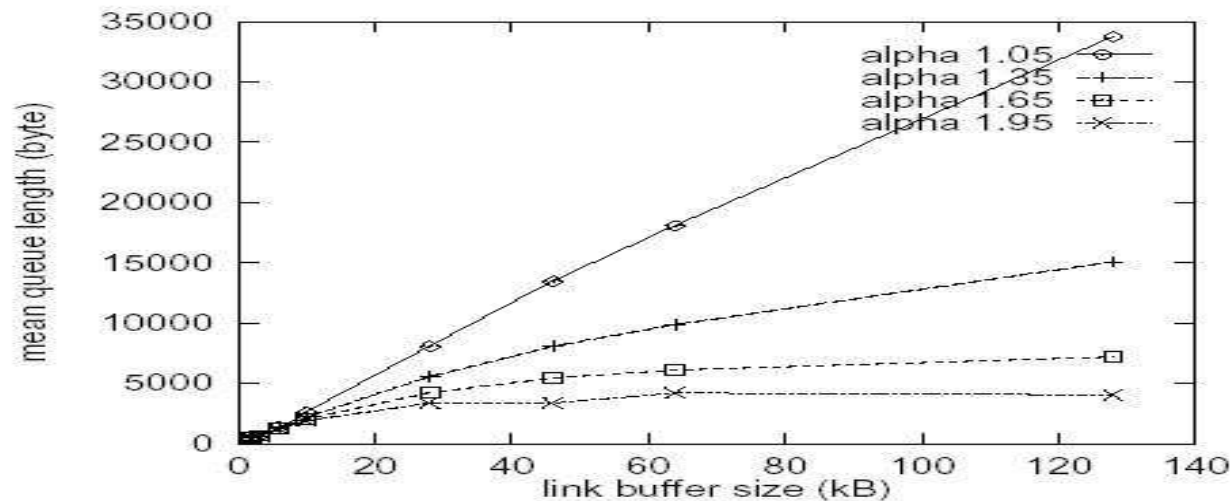
Understanding Self-Similarity (contd.)

Self-similarity manifests as,

- Slower decay of variances of sample mean than reciprocal of sample size.
- Autocorrelation decays hyperbolically than exponentially. fast.
- Spectral density is concentrated near the origin.

Effect on Network Performance

- Self-Similarity comes into picture because of longer, sustained file-transfer type of connections resulting in →
 - Reduced Throughput (Park99)
 - Greater queueing delay (Yousefi02, Fang95)
 - Larger buffers needed



Mean queue length and self-similarity (Park99)

Modeling Techniques

- ARIMA Processes
- Fractional Gaussian Noise
- Artificial Neural Networks
- Transform Expand Sample (TES)
- M/G/∞ queues

1. ARIMA Process

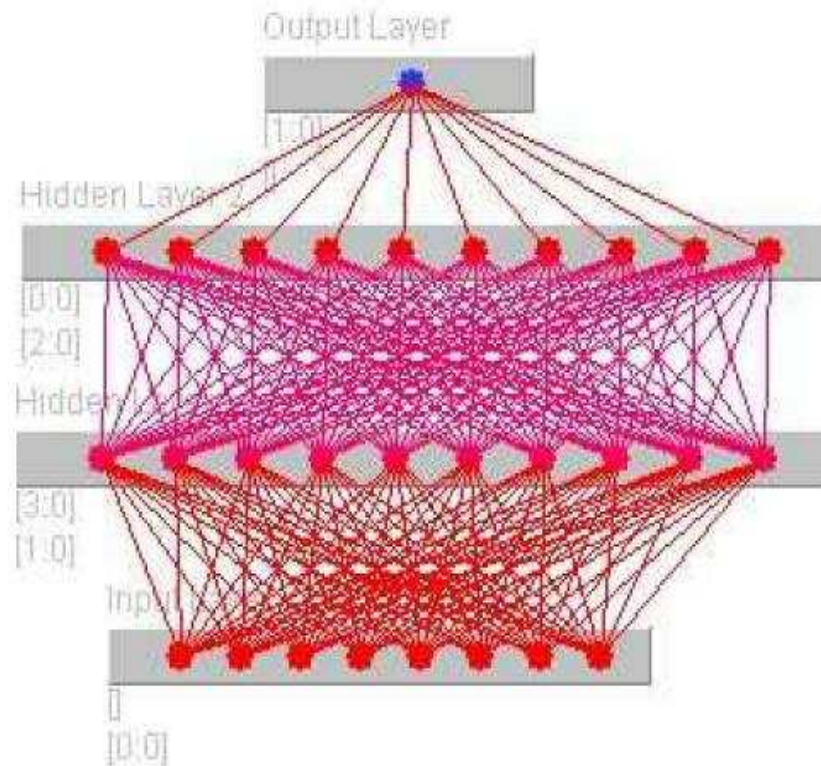
- Autoregressive Integrated Moving Average Process (Ardao00)
- Anatomy of $ARIMA(p, d, q)$ process:
 - **AR** : Each current observation as function of previous p observations.
 - **I** : d -th order differences between samples are modeled.
 - **MA** : Each current observation as function of previous q errors.
- Flexible in modeling both short-term and long-term behavior.
- Reported to be capable of generating quality traces with lesser complexity.

2. Fractional Gaussian Noise

- Most used variant(Paxson97):
 - Create the FGN power spectrum based on n , number of samples and Hurst parameter, H .
 - Perform inverse DTFT on spectrum to get the time samples, which by construction will be FGN in nature.
- Very fast due to FFT algorithm.
- Rigid correlation structure because of just three parameters, μ , σ^2 and H .

3. Artificial Neural Networks

- Universal approximation property of a neural network is used to train a neural network to mimic the self-similar traffic behavior by adjusting the internal weight of the neural network based on a finite training data (Yousefi02).



3. Artificial Neural Networks(contd.)

- Fast training algorithm for optimization process are available.
- However neural models behave arbitrarily outside the trained ranges, some enhancements suggested (Paliwal'03).

4. Transform Expand Sample(TEs)

- Tries to capture the *pdf* and *autocorrelation* structure of the empirical traffic data.
- Uses correlated stream of random numbers.
- Implemented in software, TesTool.
- Unsuitable for very heavy-tailed distributions.

5. M/G/∞ Queue-based Modeling

- Basic Idea (Erra97): To simulate a M/G/∞ queueing system with
 - Poisson arrivals (exponential inter-arrival time distribution)
 - An infinite number of servers (pure delay system)
 - A heavy-tailed service time-distribution with infinite variance, e.g. Pareto distribution:

$$(3) \quad 1 - F(x) = P[X \geq x] = cx^\alpha, x \geq \beta$$

- The traces are generated by sampling the queue length process at a suitable sampling rate.

Tools for Measurement

- Introduction
- Variance Analysis
- R/S Plots
- Wavelet Method

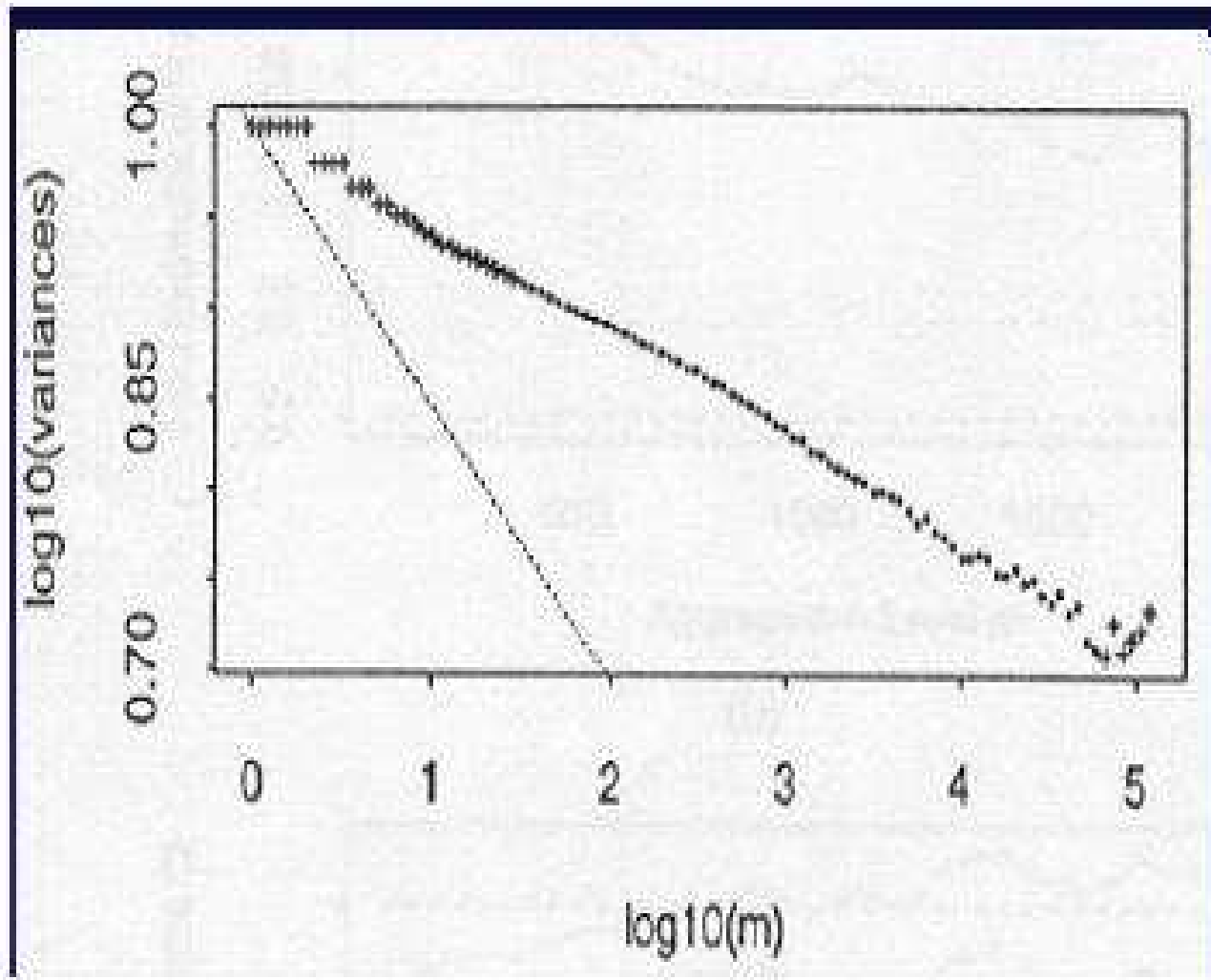
Measurement Tools : Introduction

- Three quantities of interest to be estimated,
 - Sample mean, $\hat{\mu}$
 - Sample variance, $\hat{\sigma}^2$
 - Hurst parameter, \hat{H}
- Estimation of first two fairly easy, can be done with any standard statistical tool.
- However, \hat{H} , needs special treatment.....

1. Variance Analysis

- Create aggregated processes, $X^{(m)}$, for various values of m .
- Plot $\log(\text{Var}(X^{(m)}))$ against $\log m$.
- From the slope of the plot, calculate the Hurst parameter using the relation, $\text{Var}(X^{(m)}) = \sigma^2 m^{-\beta}$.
- Useful for short-term analysis

1. Variance Analysis



(Leland94)

2. R/S Analysis

- Following quantity is computed for different n ,

$$\frac{R(n)}{S(n)} = [\max(0, W_1, W_2, \dots, W_n) - \min(0, W_1, W_2, \dots, W_n)]$$

(4)

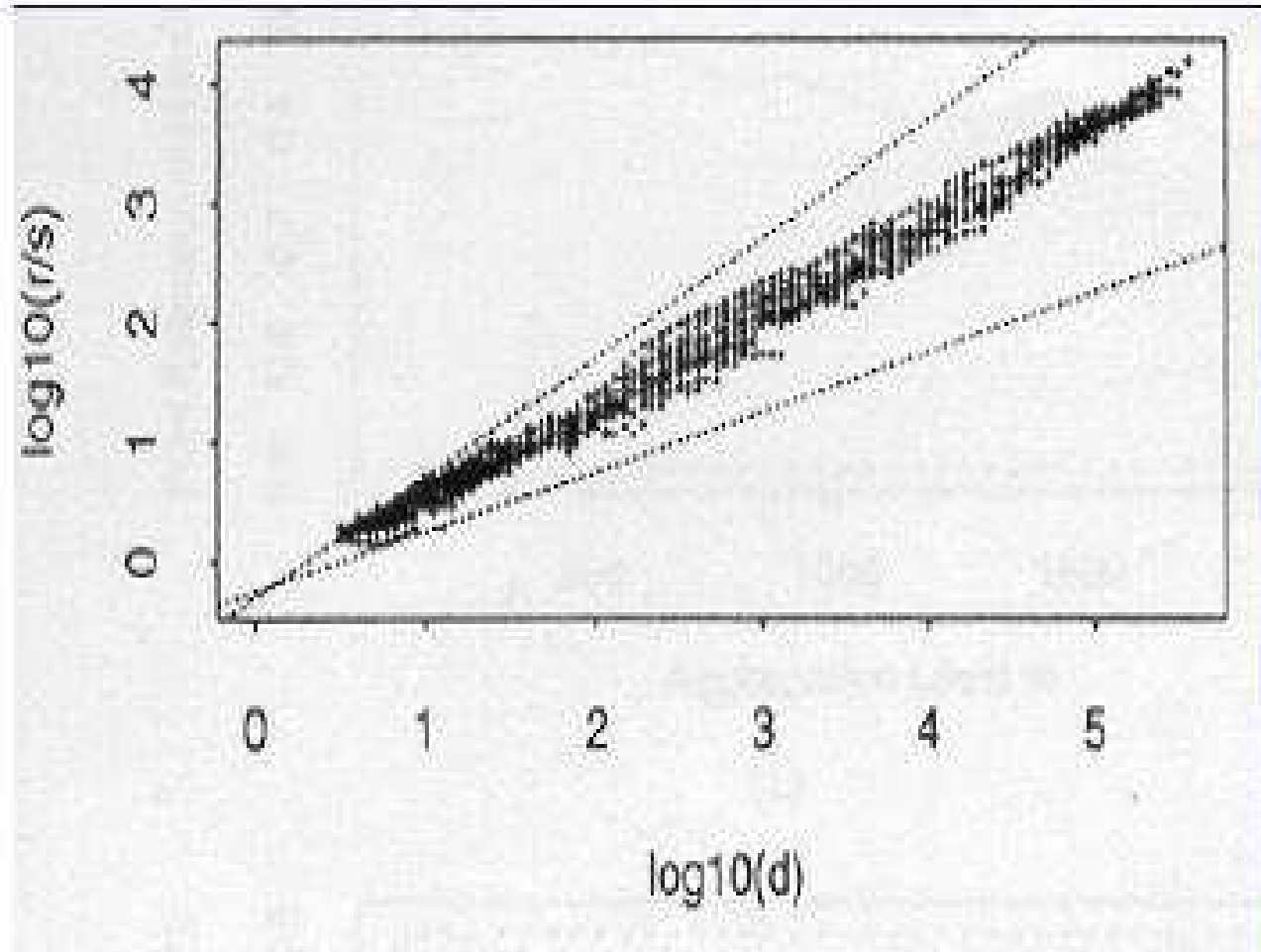
$$(5) \quad W_k = (X_1 + X_2 + \dots + X_k) - k \bar{X} .$$

- A plot of the log-statistic ($\log(R(n)/S(n))$) versus $\log n$ can be used to estimate H using,

$$(6) \quad E[R(n)/S(n)] \sim \alpha n^H$$

- Useful time-domain analysis technique.

2. R/S Analysis(contd.)



(Leland94)

3. Wavelet Method (Veitch01)

- Discrete wavelet transform is done on the time series.
- From the coefficients of the wavelet decomposition, LRD parameter is selected in suitable octaves.
- From the LRD parameter, self-similarity parameter is easily estimated using, $H = \frac{(1+\gamma)}{2}$.

My Work

- Introduction
- Modeling
- Verification

My Work : Introduction

- Aim: To select one of the modeling methodologies and implement in one of the simulation softwares.
- Design and Validation Choices
 - Modeling Methodology : M/G/ ∞ queue-based.
 - Simulation Software : GPSS
 - Verification: Wavelet-technique.

Modeling

- GPSS: A simple discrete-event simulator.
- Parameters for $M/G/\infty$ queues taken as suggested in (Erra99) for generation of self-similar traffic with $H = 0.8$.
- Simulation script written in GPSS for the desired modeling specs.
- Sampling of queue length process is done to generate self-similar traffic traces.

Modeling : GPSS script

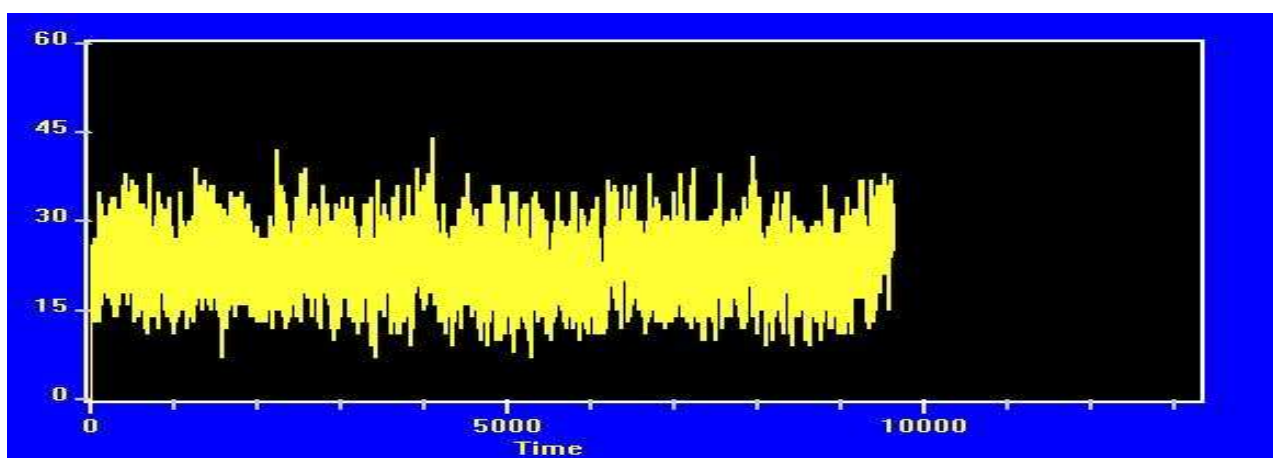
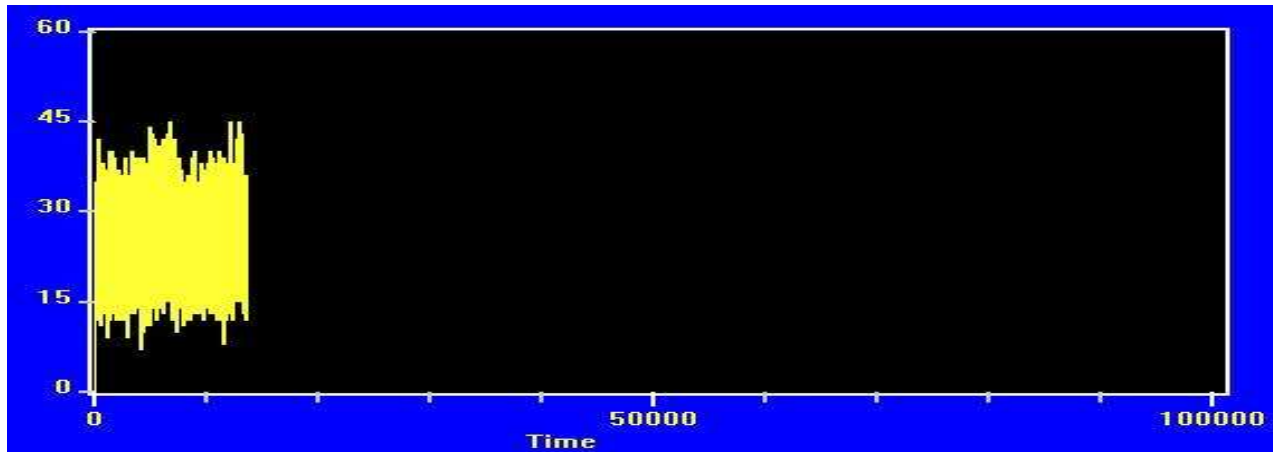
```
* Author : Vikas Paliwal
* Create Servers, assigned an arbitrarily
* large number of servers
  InfServer STORAGE 65000
* Define Variables
  ArrRate VARIABLE 1.0
  Locale VARIABLE 10
  Scale VARIABLE 1.05
* Simulation
  GENERATE (Exponential(1,0,V$ArrRate))
              ;Create next arrival.
  QUEUE      ServerQ
              ;Begin queue time.
  ENTER      InfServer
              ;Take one of the server
  DEPART     ServerQ
              ;End queue time.
  ADVANCE    (Pareto(2,V$Locale,V$Scale))
              ;Service Time
  LEAVE      InfServer
              ;Release the server

  TERMINATE
  GENERATE 0.01
              ;Ratio for sampling

  TERMINATE 1
```

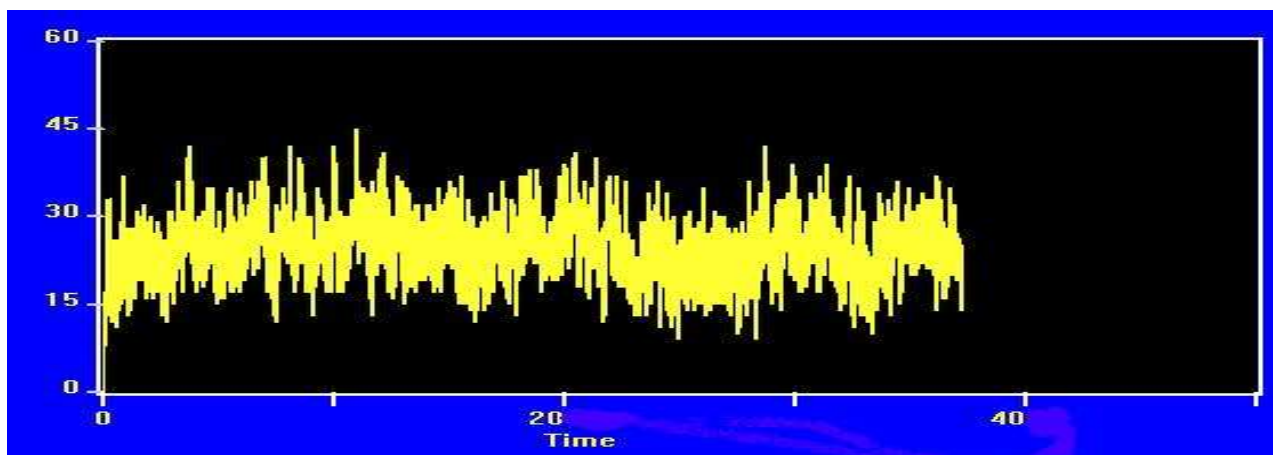
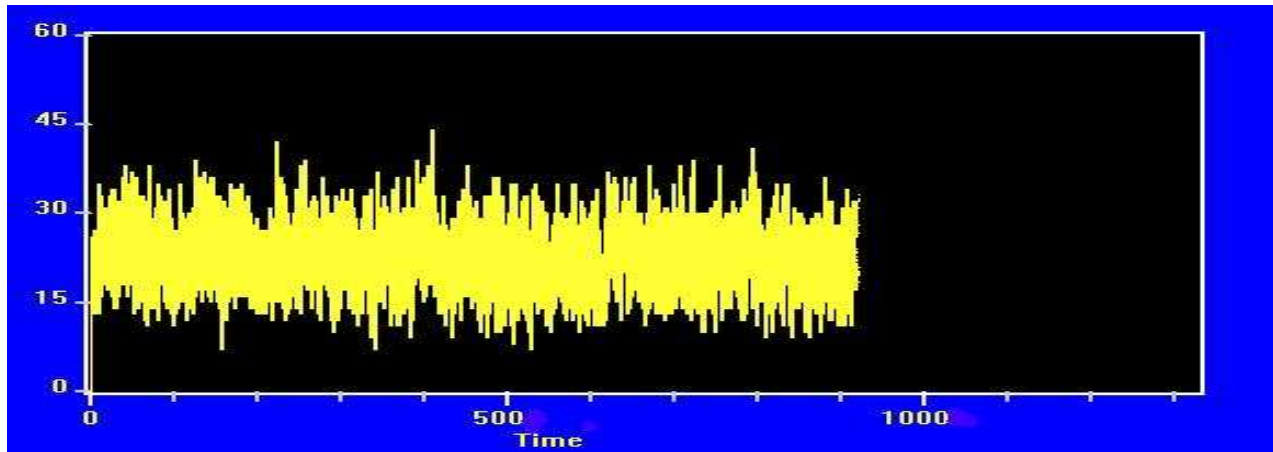
Verification

- Time units 100s and 10s



Verification(contd.)

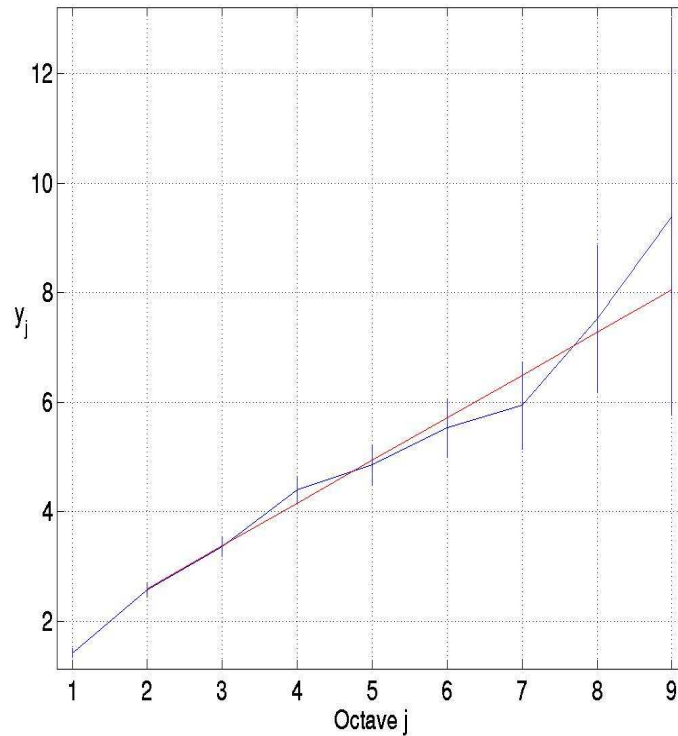
- Time units 1s and 0.1s



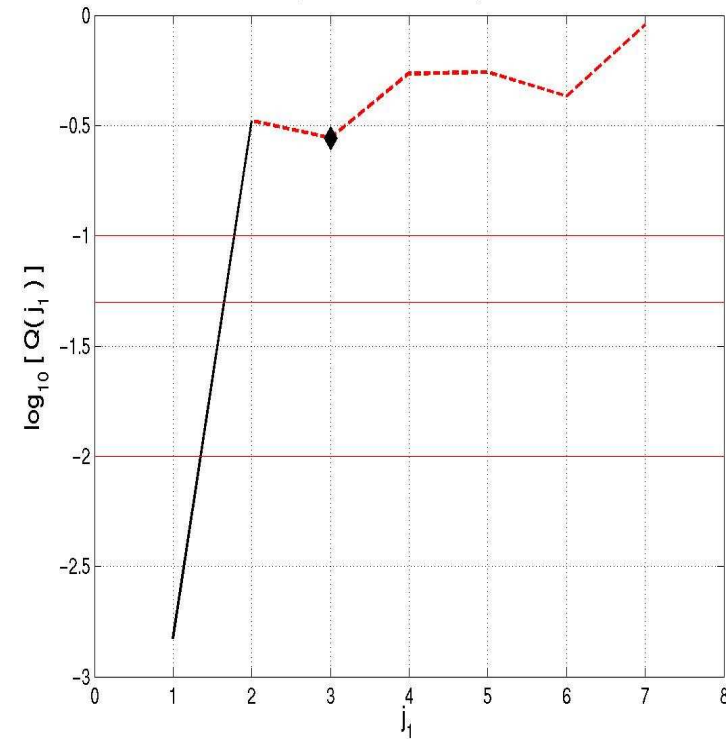
Verification: Parameter Estimation

- An implementation in MATLAB is used.

Logscale Diagram, $N=3$ $[(j_1, j_2) = (2, 9), \alpha\text{-est} = 0.781, Q = 0.33159], D\text{-init}$



Goodness of fit $Q(j_1)$, $N=3$ (symbol gives j_1^* using method 6), $D\text{-init}$



Verification

- Value of Hurst parameter using developed model(0.7994) and initial value(0.8) are in close agreement
- The developed traffic model exhibits visual self-similarity.

Conclusions

- Accurate modeling of self-similar behavior of network traffic important for performance analysis of networks.
- Research is ongoing to develop a robust model for self-similar traffic generator.
- FGN and pareto-distribution based generators most widely used because of their inherent simplicity.
- However, developing a model that covers broader range of traffic patterns still a good potential research area.
- M/G/∞-queue-based technique offers a simple and easy-to-implement approach for self-similar traffic data generation.

Conclusion

- A formalism for a critical study of various self-similar traffic generation schemes is developed.
- A modeling technique is implemented and verified.

Most Relevant References

- **Park99:** K. Park, G. Kim, and M. Crovella, "On the effect of traffic self-similarity on network performance", in Proc. SPIE International Conference on Performance and Control of Network Systems, November, 1997.
- **Paxson95:** Vern Paxson and Sally Floyd, "Wide-Area Traffic: The Failure of Poisson Modeling", IEEE/ACM Transactions on Networking, Vol. 3 No. 3, pp. 226-244, June 1995.
- **Leland94:** Will Leland, Murad Taqqu, Walter Willinger, and Daniel Wilson, "On the Self-Similar Nature of Ethernet Traffic (Extended Version)", IEEE/ACM Transactions on Networking, Vol. 2, No. 1, pp. 1-15, February 1994.
- **Crovella99:** Mark E. Crovella and Azer Bestavros, "Self-Similarity in World Wide Web Traffic: Evidence and Possible Causes", IEEE/ACM Transactions on Networking, 5(6):835-846, December 1997.
- **Yousefi02:** Homayoun Yousefi 'zadeh "Neural Network Modeling of Self-Similar Teletraffic Patterns" Invited Paper, In Proceedings of the First Workshop on Fractals and Self-Similarity, The 8-th ACM SIGKDD Conference on Knowledge Discovery and Data Mining, July 2002.

References(contd.)

- **Fang95:** Y. Fang, M. Devetsikiotis, I. Lambadaris, and A. R. Kaye, "Exponential Bounding Techniques for the Waiting Time Distribution of TES/GI/1 Queues", 1995 ACM SIGMETRICS and Performance '95, May 1995, Ottawa, Canada.
- **Ardao00:** J. C. Ardao, C. Garcia, R. Rubio, "On the use of self-similar processes in network simulation", ACM Transactions on Modeling and Computer Simulation (TOMACS), April 2000, vol. 10, pp 125-151.
- **Paliwal03 :** V. Paliwal, Q. J. Zhang, "Modeling using Extrapolated Neural Networks", IEEE-APM Conference'2003, Seoul , South Korea, November 2003.
- **Erra97** A. Erramilli, P. Pruthi, W. Willinger, "Fast and Physically based generation of self-similar network traffic with application to ATM performance evaluation", Proc. of Winter Conf. on Simulation and Modeling, Nov. 1997.
- **Veitch01:** D. Veitch, P. Abry, A wavelet based joint estimator for the parameters of LRD, "Special issue on Multiscale Statistical Signal Analysis and its Applications" IEEE Trans. Info. Th. April 1999, Volume 45, No.3, 1999.