# Neural Network Estimation of Packet Arrival Rate in Self-Similar Queuing Systems

Homayoun Yousefi'zadeh
Department of EECS
University of California, Irvine
hyousefi@uci.edu

# Problem Statement

- Objective: Estimating Average Queuing Delay in ATM Systems

- Approach: Utilizing A Neural Network Prediction Scheme to Estimate Packet Arrival Rate Dynamically

# Self-Similarity

- Structural Similarities across a Wide Range of Time Scales
- Properties
  - Slowly Decaying Var's

    $var(X^{(m)})_{m\to\infty} \sim k_2 m^{(-b)}, \quad 0 < b < 1$
  - Long Range Dependence

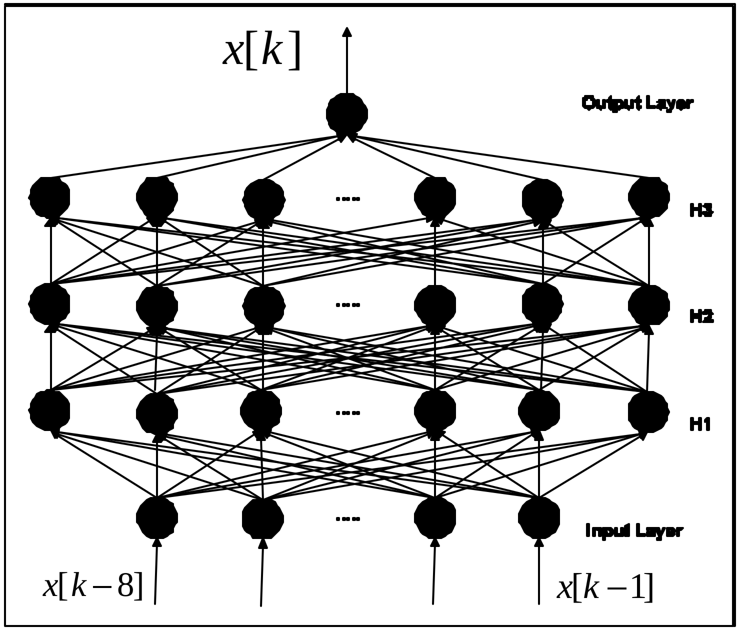
    Auto-Correlation Sum $\sum_n R(n) = \infty$
  - $1/f$ Noise Property

    $f(l)_{l\to\infty} = k_3 l^{-g}, \quad 0 < g < 1$
- Teletraffic Patterns Exhibit Fractal Behavior w/ No Actual Burst Length
- Traffic Evidence
  - Ethernet LAN: Leland
  - ISDN: Hellstern
  - VBR Video: Beran
  - CCSN: Duffy

# Self-Similar Teletraffic Modeling

- Statistical Approach
  - Leland, Willinger, Taqq, Willson
- Chaotic Systems Approach
  - Erramilli, Singh, Prutti
- Neural Network (NN) Approach
  - Yousefi'zadeh, Jonckheere

  - Fully Connected
  - Feed Forward
  - BPA Learning
  - Inputs:
    $x[k-8]$ thru $x[k-1]$
  - 3 Hidden Layers
    w/ 20 PEs Each
  - Output: $x[k]$



# Back Propagation Algorithm

- Start from an Initial Set of Weighting Functions
- Do {
  - Propagate Forward from Input $u$ to Output $J$
  - Calculate Absolute Output Error $E = \frac{1}{2}\sum_k (u_k - J_k)^2$ and Calculate Backward Scaled Relative Errors of Each PE

    $$e_j[s] = x_j[s].(1 - x_j[s]).\sum_k \{e_k[s+1].w_{kj}[s+1]\}$$
  - Calculate per PE Variations of Weighting Functions

    $$\underbrace{\Delta w_{ji}[s]}_{(k+1)-thstep} = lc.e_j[s].\{x_i[s-1] + k.e_i[s-1]\} + M(\underbrace{\Delta w_{ji}[s]}_{k-thstep})$$

} While ( Error > Bound )

BPA Complexity: Time $O(IN)$ Space $O(N)$

# Self-Similar Traffic Generation

- Artificial On-Off Source Model: Intermittency Maps

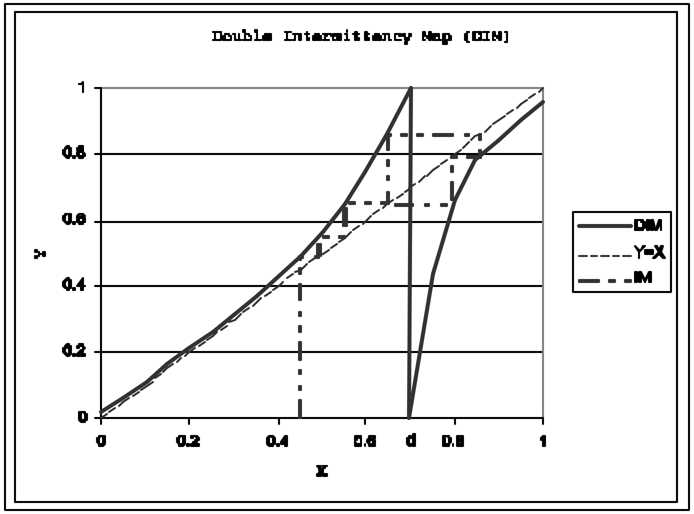
$$x_{n+1} = \begin{cases} e_1 + x_n + c_1 x_n^m, & 0 \le x_n \le d \\ -e_2 + x_n + c_2 (1 - x_n)^m, & d \le x_n \le 1 \end{cases}$$

$$e_1 = 0.01,\ e_2 = 0.05,\ \ m = 5$$

$$c_1 = 1.73,\ c_2 = 267.49$$

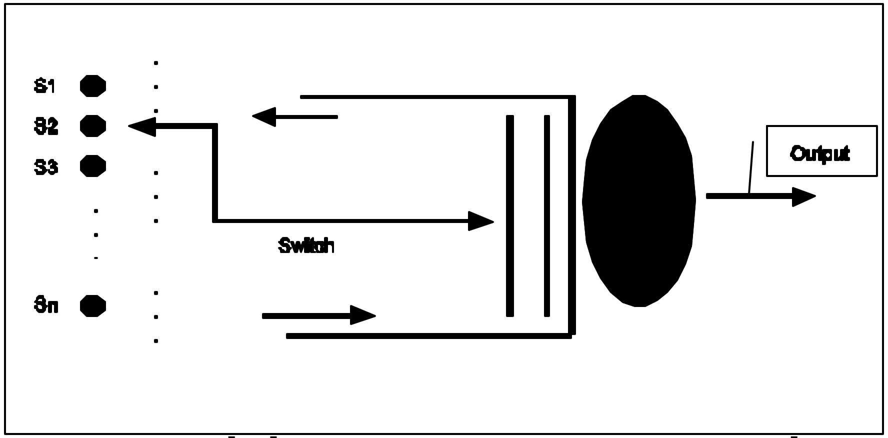
$$x_0 \in [0.1, 0.3],\ d = 0.7$$

- Threshold-Based Transition of State from Active to Passive State and Vice-Versa



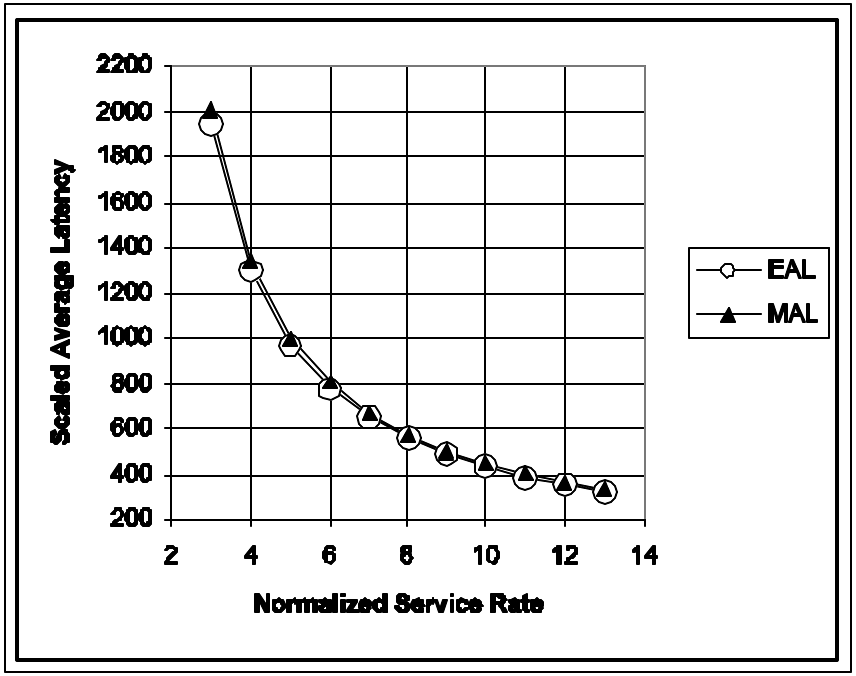

- NN Modeling of DIM or Normalized Continuous Traffic Samples

# Experiment Setup




- Sources n=3 with 120 DIMs Each
- Burst Scale ATM (FIFO) Queuing
- STDM (Shared Service Rates, e.g., ATM VCs) Scheduling
- Fixed Service Rate, Negligible Buffer Loss
- Complete-Sharing Buffer Mgmt

# Simulation Results




EAL: NN Estimated Avg. Latency    MAL: Measured Avg. Latency

# Numerical Issues

- Time Consuming Learning Algorithm due to Dynamics Complexity
- Iterative Learning Is Required as the Result of Facing Chaotic Divergence
- Impact of Initial Weighting Functions of NN in the Algorithm Convergence

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