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Analysis Self Similarity Traffic in Next Generation Networks

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***Abstract*— Ubiquitous IP based Next Generation Networks characterized by seamless mobility. According to the Received Signal Strength (RSS) mobile terminal in the network will be roaming in the vicinity of the heterogeneous wireless network and have frequent handover from one technology\ to another. As there is frequent handoff from one technology to another,the performance of the mobile terminal in the network will degrade bue to non-availability resources. Moreover network infrastructure has to handle a huge amount of IP traffic, including significant realtime traffic with guarantied**

Quality of Service (QoS).The stringent Quality of Service (QoS) parameters like delay, delay variance and packet loss will also be affected. Traffic models is a mathematical approximation for real traffic behavior can account traffic in the network and this can be used as input to analysis resource allocation strategies, reduce end to end delay, packet loss and jitters in the NGN environment to meet the QoS given by the Service Level Agreement(SLA).Real time network traffic is complex, as it exhibits strong dependencies. Self-similarity with high variability and therefore classical models of time series such as Poisson and Markov processes are not appropriate for modeling. These models will underestimate the burrstones of traffic. Self similarity models like Fractional Gaussian Noise(FGN),Fractional Brownian Motion (fBM),Fractional-ARIMA and M=G=1 can represent the high variability in the traffic. From these model FARIMA will best fit for the high priority real time VBR traffic. FARIMA can represent the coexistence of SRD and LRD along with stability innovation. Future traffic in the network can be predicted from present and past history. According to predicted value, resource mainly bandwidth can dynamically allocated on demand.

***Keywords:* -- Self similarity models, FARIMA, QoS, NGN, Heavy tailed distribution**

I. INTRODUCTION

Next generation networks are packet based IP network, major challenge in the network is to provide quality of service(QoS).The stringent QoS demands for a high guaranteed bandwidth and should guarantee high utilization, minimum packet loss and delay. To ensure the QoS in the network statistical characteristic of telegraphic systems has been models. The traffic model is a mathematical approximation for real traffic behavior. If the traffic models do not represent actultraffic, one may overestimate or underestimate the performance in the network. The real time multimedia traffic in high speed network traffic exhibits self similar (or fractal) properties over a wide range of time scales [1].The properties of self-similar teletraffic are very different from traditional models based on Poisson, Markov modulated Poisson, and related processes. The use of traditional models in networks characterized by self-similar processes can lead to incorrect conclusion, the performance may over-estimate the performance in the computer networks, insufficient allocation of communication and data processing resource. Highly variable input traffic from the network is bursty in nature. The bursty traffic in the network can be represented as continuous or discrete stochastic process Xt for packet arrival time t1; t2; :; :; tn. Burstiness in the network can be represented with long range dependency and using Hurst parameter [12] value can be estimated.

This paper is organized as follows. Section II about failure of Poission model , section III the mathematical representation of self-similarity followed different self similar model. Analysis of FARIMA model and presents validation results.

II. FAILURE OF POISSION TRAFFIC MODEL

Most widely used and oldest traffic model is the memoryless Poisson Model, this model characterize the inter-arrival times are by exponentially distributed with a rate parameter _ [6].Probability distribution is given by

$$P(A(t+x) - A(t) = \frac{(\lambda x)^n e^{-\lambda x}}{n!}$$

IP based traffic in the high speed networks shows high variability over wide range of traffic and aggregated traffic from the input source exhibits burrstones. Traditional traffic model like Poisson process unable to capture traffic burrstones which characterize real time traffic. The aggregated traffic that can be packet interracial times or packet size are described by marginal distributions with heavier tail than that of the exponential. The aggregated sample will approach normal distribution and mean value will smooth towards to zero as shown in fig 1.

$$P(T_n > t + x / T_n > t) = \frac{P(T_n > t + x)}{P(T_n > t)} = \frac{e^{-\lambda(t+x)}}{e^{-\lambda t}} = e^{-\lambda x}$$

The Poisson model suitable for limited variability in both time and space independent or have temporal correlations

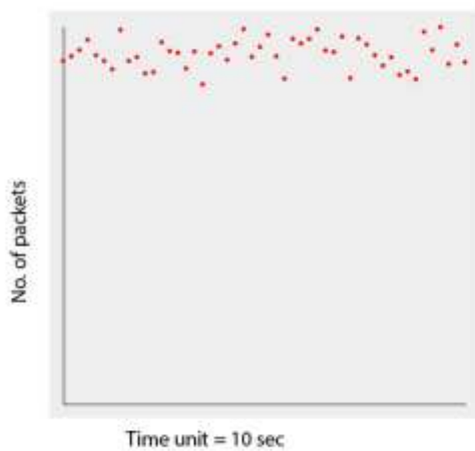

Fig. 1. Aggregated Poission Distribution

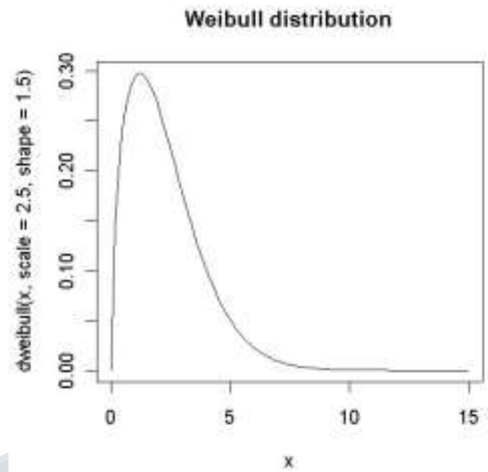

Fig. 2. Heavy Tailed Distribution

That decay exponentially fast. If the high variability shows non Gaussian bursty traffic possess heavy tailed marginal distributions characterized heavy tailed as shown in fig:2 and modeled with memeoryless Poisson distribution huge variation (with strong correlation)will smooth out and performance in the network will get degraded [3], [4] and the tail of the distribution decays hyperbolically.

P[X > x] _ x□_

Where X has a distribution with a heavy tail with tail index _ and the distribution will be skewed to left as shown in fig: 2

The distributions have infinite variance; reflect the extremely high variability that they capture. Poisson processes which lose their burstiness and flatten out when time scales are changed.

III. INTRODUCTION TO SELF SIMILARITY

IP traffic are characterized by high or extreme variability [1] [4].Statistically, temporal high variability can be captured by long-range dependences that is, autocorrelation exhibiting power-law decay and spatial variability can be described through heavy-tailed distributions with the Pareto distributions. The high variability in space and time manifest self-similarity behavior. A stochastic random process X(t); t 2 R with index H > 0,for all a > 0,X(t); t 2 R d= aHX(at)R H,hurst parameter that determine degree of self similarity and value will be ranging 1 2 > H > 1,as H ! 1 the degree of both self-similarity and long-range dependence increases. The asymptotically and exactly second-order processes are characterized by autocorrelation function which decay hyperbolically.If _mx

(k) = _x;m ! 1,the process is called asymptotically second-order self-similar and for exactly second order self similar processes _mx

(k) = _x; k _ 0,this implying that the sum of auto correlation diverge. Main features of self similarity are1: slowly decaying variance 2: the auto correlation is not summable 3: spectral density obey power law in the orgin [2].Self similarity along with long range dependency and the heavy tailed distribution has got significant impact in the performance analysis of the network [1], [6].

A. M=G=1 Model

M=G=1 aysmptotic self similar system is the most basic and fundamental model which has Poisson arrivals, Pareto distributed holding time and an infinite servers system. These models versatile enough to capture both long and short correlation traffic in the network. M=G=1 model will generate slot sizes represent both probability distribution and correlation structure in the estimated traffic trace. The input process (_; _) extremely correlation structure. The input sequence Pareto distribution with finite mean and infinite variance of service times. The correlation structure of the dependent random value Xn; n = 0; 1; ::: is controlled by the Gof _. The covariance is given by jcovXn+j ;Xnj = _ 2E[_; _ + 1]. If variance is finite then it is short-range dependent and for long range dependent variance is infinite. The Poisson marginal's of the M=G=1 process were transformed Gamma/Pareto distribution.

B. Fractional Brownian Motion and Fractional Gaussian Noise

The Fractional Browian Motion model has been [17] identified as an efficient way for modeling and generating LRD traffic. Fractional Browian Motion is a continuous-time Gaussian process BH (t).Increment of FBM can be represented a Fractional Gaussian Noise X = (Xk : k _ 1) with Hurst parameter H[0:5; 1],mean _,variance _2, and Autocorrelation function Xn;Xn+k = 1 2 (jK + 1j2H □ 2jkj2H + jk □ 1j2H).To capture the self-similar traffic processes, Norros []proposed a traffic model of Fractional Brownian Motion, which is defined as A(t) = Mt+ p a MBH(t); t _ 1 where A(t) represents the number of packets that enter the network at[0; t]. For exactly second order self similar processes _mx (k) = _x; k _ 0,this implying that the sum of auto correlation diverge. The covariance function (:) decays hyperbolically as _(X) _ ck_.

If the arrival process is a fractional Brownian motion, then the queue length distribution is Weibullian, decays as power law as P[X _ x] ' exp(□) The fBM is a parsimonies model for bursty traffic. The fractal property are addressed in this model. But the coexistence of both LRD and SRD in the real time VBR traffic.FGN is one of the simplest examples of long range dependent time series with three parameters, mean, variance, and Hurst parameter H.

IV. PROPOSED MODEL

A. Fractional ARIMA Time Series model

The fractional autoregressive integrated moving average (FARIMA) is an asymptotic self-similar model with the ability to capture both the short-range dependent (SRD) and long-range dependent (LRD) characteristics. The traditional models like autoregressive (AR) and autoregressive moving average (ARMA), are not able to capture the self-similar characteristic of the traffic in networks. The FARIMA model is used to generate artificial traces of traffic with required Hurst value.

The autocorrelation function of the artificial traffic is also compared with that of the real traffic to verify the goodness of fit [?].The marginal distribution of the FARIMA model can be controlled by using _ generating the model.

B. Traffic Modelling And Prediction Using FARIMA Time Series Models

FARIMA an asymptotically second order self similarity is an extension of ARIMA time series model [15], [12].This is a class of long memory that can explicitly account for persistence to incorporate the long term correlation in the data. Compare to other times series model FARIMA models can simulate an autocorrelation with short-range dependencies at small lags as well as long-range dependencies for long lag. The short range dependency defined by (p,q) is an ARMA model and long range dependency definited by d along with high variability heavy tailed distribution parameter _ .The traffic is having infinite variance the value of tail index can be calculated as H = d + 1=_ and for finite variance H = d + 1=2.The aggregated traffic in the network can be considered as stochastic time series processes Xt; t = :::;□1; 0; 1; 2:::.This series can be described as an FARIMA(p,d,q) process with _(B)_dXt = _(B)at where at; t = :::;□1; 0; 1; 2::: is a white noise with mean 0 and variance _2 .Both _(B) and _(B) are polynomials in complex variables with no common zeros and _d fractional differencing operator defined by means of binomial expansion. The degree of differencing d is allowed to take nonintegeral values.

The high bursty traffic can be modelled by transferring the FARIMA problem to an ARMA problem.Estimate the parameter d [11]using R=S method.The tail index is having small value so this will not have any significance impact in d,so this value is ignored. From the real time VBR traffic the FARIMA parameter (p; q) and d value had been estimated ARMA(2,1) and d value as 0:36,_1; _2 and _1, as shown in table 1

Table I
Parameter estimated for FARIMA

Model	ϕ	θ	d
FARIMA(2,0.36.1)	(0.88,0.01)	0.77	0.46

FARIMA(p,d,q) model to predict the future values of a time series from current and past value. The time series

Algorithm 1 Algorithm:For fitting FARIMA time series model

1.Pre-processing the measured traffic trace to get zero-mean time series X_t
2.Obtaining an approximate value of d according to the relationship $d = H - 0.5$ [11]
3.Calculate $Y_t = \nabla^d X_t$
4.Apply the Box-Jenkins algorithm [15]$\phi(B)$ and $\theta(B)$ of the ARMA(p,q) model

$$\phi(B)Y_t = \theta(B)a_t$$

5.Model identification: Determining p and q for fitting ARMA models
6.If residual value is a white noise,go to 7 else repeat step5
7.Estimate parameters $\phi(p)$and $\theta(q)$

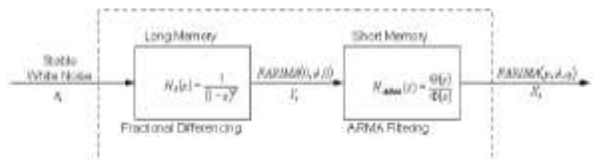

Fig. 3. Modeling with FARIMA Time Series Model

Xt; t = ::: □ 1; 0; 1::.The causality and invertibility in the time series can be written as

$$X_t = \sum_{j=0}^{\infty} \psi_j a_{i-j}$$

$$a_t = \sum_{j=0}^{\infty} \pi_j X_{i-j}$$

where

$$\sum_{j=0}^{\infty} \psi_j = \theta(B)\phi^{-1}(B)\Delta^{-d}$$

and

$$\sum_{j=0}^{\infty} \pi_j = \theta^{-1}(B)\phi(B)\Delta^{d}$$

Linear prediction can be done with FARIMA model. Let Xt^(h) denote the h-step forecast made at at some future time t + h (h is called the lead origin t)

$$X_t = \sum_{j=0}^{\infty} \psi_j a_{i-j}$$

Linear prediction for FARIMA can be calculated with

$$X_t\hat{(}h) = \sum_{j=0}^{\infty} \pi_j X\hat{_{i-j}}$$

The mean squared error of the h-step forecast

$$\hat{\sigma^2}(h) = E(X_{t+h} - X\hat{_{i-j}})^2 = \sigma^2 \sum_{j=0}^{h-1} \psi_j^2$$

H-step forecast by adding a biase value __ with ^X t. FARIMA is fitted with (2; 0:36; 1).The h step forecast is calculated as shown in Fig:4 For call admission control using predic-

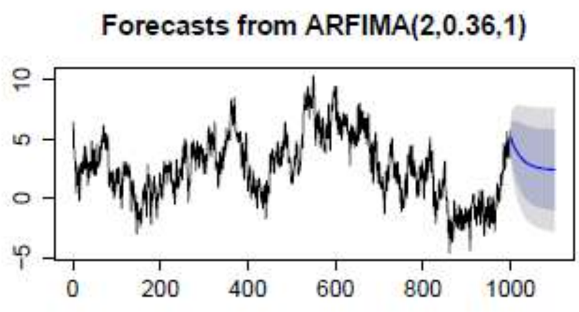

Fig. 4. Forecast for video traffic ion,

Calculate value should be the upper probability limit to specify the accuracy of traffic prediction since the lower limit does not contribute to any packet loss probability. Predict the next value of time series using mean squared error by adding

ξ_μ

$$\hat{X}_t^\mu = \hat{X}_t + \xi_\mu$$

where

$$P[e_1(h) < \xi_\mu] = \mu, 0.5 > \mu > 1$$

For the traffic model traffic prediction one-step, time unit = 0.1 second under the upper probability limit 85% .

V. COMPARISION OF DIFFERENT TRAFFIC MODEL

The failure of the traditional Poisson models to capture the long range dependence (LRD) and the burstiness of such packet arrival processes. The presence of correlations and burstiness over many time scales have a considerable impact on the queuing performance. Burstiness in traffic models can be modeled with Fractional Brownian Motion (FBM) models, FARIMA models, M=G=1 models, on/off models, etc. to capture LRD and self-similar properties. M=G=1 capture both long and short correlation traffic in the network. Short Range Dependence (SRD) if its auto-correlation function is integrable, and is said to display Long Range Dependence (LRD) if its auto-correlation function is non-integrable. Farima(p; d; q) process are either Gaussian or non –Gaussian with finite or infinite variance, replicate the marginals and both the short range and long range correlations of real time VBR traffic. FARIMA model the performance is much sensitive to the buffer size .When the incoming traffic is strongly correlated and/or burst the decay rate be much slower than an exponential which leads to inaccurate in the estimation of the buffer size.

Real time VBR bursty network traffic is complex in next generation, as it exhibits strong dependence and self similarity, models of time series such as Poisson and Markov processes are not appropriate for its modeling. Maintaining high utilization of the bandwidth is the objective for

Table ii
Comparison of different traffic model

Model	ACF	Timeofexecution	Queueing Performance
$M/G/\infty$	$e^{-\beta\sqrt{(k)}}$	$O(n)$	Gamma/Pareto Distribution
FGN	$e^{-\beta log(k)}$	$O(n)^2$	Poisson Marginal
FARIMA	$e^{-\beta(k)}$	$O(n)^2$	Poisson Marginal Distribution

Efficient traffic management, which include CAC, policing, scheduling, buffer management, and congestion control etc. The high variable and highly correlated VBR traffic in the network can be modeled with self similarity models like FARIMA,M=G=1 ,FGN. Mostly VBR traffic in the network exhibits both short range and long range dependency along with heavy tailed distribution can be modeled with FARIMA time series model with parameter (p; d □ 1=_; q). FARIMA time series traffic model can predict traffic and allocate bandwidth dynamically. This model is flexible enough to parsimoniously capture the statistical property of traffic can allocate bandwidth on demand and mathematically.

VI. CONCLUSION

High speed traffic in the next generation network is bursty in nature. Tradtional models like Markovin, Poission or time series models like AR,ARIMA are inapproprate to model the highly correlated traffic .Self similar traffic models like M=G=1,FARIMA and fBM are appropriate models that can represent self similarity fractal property in traffic behaviour. M=G=1 capture both short-term and longterm correlations ,hence combining the goodness of Markovian models at small lags with that of LRD models at large lags. Queueing tail can be represented with Poission/Gamma distribution. The FBM model an exactly self similar model can represent the LRD and this model are inappropriate to model the real traffic trace. FARIMA model is able to represent the highly correlated traffic with high variance with parameter (p; d□1=_; q). FARIMA time series traffic model can predict traffic and allocate bandwidth dynamically. This model is flexible enough to parsimoniously capture the statistical property of traffic and can allocate bandwidth on demand .

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