A Survey on the Common Network Traffic Sources Models

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Abstract

Selecting the appropriate traffic model can lead to successful design of computer networks. The more accurate the traffic model is the better the system quantified in terms of its performance. Successful design leads to enhancement the overall performance of the whole of network. In literature, there is innumerous traffic models proposed for understanding and analyzing the traffic characteristics of computer networks. Consequently, the study of traffic models to understand the features of the models and identify eventually the best traffic model, for a concerned environment has become a crucial and lucrative task. Good traffic modeling is also a basic requirement for accurate capacity planning. This paper provides an overview of some of the widely used network traffic models, highlighting the core features of these models and traffic characteristics. Finally we found that the N_BURST traffic model can capture the traffic characteristics of most types of computer networks.

Keywords: Traffic Modeling, Stochastic Process, Queue Theory, Chaotic Maps, Performance, Quality of Service, Poisson Process, Markova Process.

1.INTRODUCTION

Why modeling traffic? In general, traffic modeling aims to provide the computer network designer with relatively simple means to characterize traffic load on a computer network. Ideally, such means can be used to estimate performance and to enable efficient provisioning of network resources. Modeling a traffic stream emitted from source or traffic stream that represents a multiplexing of many Internet traffic streams is part of traffic modeling. It is normally reduced to finding a stochastic process that behaves like the real traffic stream from the point of view of the way it affects computer network performance. The more accurate the traffic model is the better the system quantified in terms of its performance. Traffic modeling should focus on capturing the aspects of the application which posts special demand on the system performance in the traffic model case, the long rang dependency (LRD) is the key characteristic that needs to be captured, because high burstiness resulting from LRD posts high demand on both transport and buffering capability in the system. Some network applications are real-time and some are non-real-time applications. In this paper, we are interested in real–time computer network applications. Some real time network applications are bursty and dynamically change their bandwidth demands overtime (e.g., compressed video), while others require constant bandwidth (e.g., uncompressed video). Bursty applications produce VBR (Variable Bit Rate) traffic streams, while constant applications produce CBR (Constant Bit Rate)traffic streams. In the literature there are many research in traffic model classification in [1,2] the authors divided traffic models into stationary and non stationary. Stationary traffic models can be classified into two classes: short range and long-range dependent. Traffic can be as above VBR or CBR. CBR (smooth) traffic is easy to model and predict its impact on the performance of the network. VBR (bursty) traffic models can be classify as packet level traffic models and burst (customer) level traffic model [3], where individual customers represented by individual packets rather than packet level where individual customers represent complete bursts rather than individual packets. In this paper, we classify VBR traffic models into two main categories the first category is bound (envelope) based source model, these models provide a bound or an envelope on the volume of source traffic characteristics, the bounding characterization can be deterministic or stochastic bound interval independent, bound interval dependent(BIND). The second category is unbound (exact) source model, these models characterize source behavior by describing their stochastic properties through suitable distribution functions and this category is divided into many subcategory, the last recent type of traffic model is models that use chaotic map to generate bursty traffic. We insert this type as a subcategory of the unbound category. The characteristics of chaotic map present the researchers with a method to model the non-linear nature of network traffic and make chaotic map to be a main way to generate network traffic. An overview of the progress made using chaotic maps to model individual and aggregated self-similar traffic is presented by Mondragón [6]. The organization of the rest of paper is as follows, section 2 describes traffic models and its need in design of computer network and section 3 is the conclusion.

2. TRAFFIC MODELS

The design of robust and reliable computer networks and network services is becoming increasingly difficult in today's world. The only path to achieve this goal is to develop a detailed understanding of the traffic characteristics. An accurate estimation of the computer network performance is vital. Networks, whether voice or data, are designed around many different variables. Managing the performance of computer networks involves optimizing the way networks function in an effort to maximize capacity, minimize latency and offer high reliability regardless of bandwidth available and occurrence of failures. Network performance management consists of tasks like measuring, modeling, planning and optimizing computer networks to ensure that they carry traffic with the speed, capacity and reliability that is expected by the applications using the network or required in a particular scenario. The term Quality of Service, in the field of networking, refers to control procedures that can provide a guaranteed level of performance to data flows in accordance to requests from an application/user using the network. A network that provides supports QOS usually agrees on a traffic contract with an application and reserves a finite capacity in the network nodes, based on the contract, during the session establishment phase. While the session is in progress, the computer network strives to adhere to the contract by monitoring and ensuring that the QOS guarantees are met. The reserved capacities are released subsequently after the session. There are several factors that might affect such QOS guarantees. Hence, to design a network to support QOS is not an easy task. The primary step is to once again have a clear understanding of the traffic in the network. Without a clear understanding of the traffic and the applications that might be using the network, QOS guarantees cannot be provided. Therefore, modeling of traffic becomes a crucial and necessary step. Analysis of the traffic provides information like the average load, the bandwidth requirements for different applications, and numerous other details. Traffic models enables network designers to make assumptions about the networks being designed based on past experience and also enable prediction of performance for future requirements. Traffic models are used in two fundamental ways: (1) as part of an analytical model or (2) to drive a Discrete Event Simulation (DES). Here we describe in details the most common traffic models.

2.1 BOUND (ENVELOPE) SOURCE TRAFFIC MODELS

These models provide abound or an envelope on the volume of source traffic characteristics, the bounding characterization can be deterministic or stochastic bound interval independent, bound interval dependent (BIND). As mentioned above this model can be divided into two subcategories, bound interval dependent and bound interval independent. Each subcategory can be deterministic or stochastic we describe in details here.

2.1.1 Deterministic Bound Interval Independent

Deterministic traffic modals that provide some means of bounding source peak and average bandwidth over an averaging interval such models are not only practical but they also result in an analysis that doesn't suffer from many of problems of stochastic traffic models. A traffic model for a deterministic service has several fundamental requirements. First, the model must be a worst-case characterization of the source to provide an absolute upper bound on a source's packet arrivals. Second, the model must be parameterized so that a source can efficiently specify its traffic Characterization to the network. Next, the model should characterize the traffic as accurately as possible so that the admission control algorithms do not overestimate the resources required by the connection. A worst-case representation of a traffic source may be described as follows. If the actual traffic of a connection is given by a function A such that A[τ , t+τ] denotes the traffic arrivals in the time interval [τ , t+τ], an upper bound on A can be given by a function A* if for all times τ ≥0 and all t ≥0 the following holds [38, 18].

$$A[\tau, \tau + t] \leq A^*(t). \qquad (1)$$

We refer to a function A* (t) that satisfies the property in (1) as a traffic constraint function. Note that a traffic constraint function provides a time-invariant bound on A, so that a source is bounded for every interval of length t. In practice, a source specifies its traffic characterization with a parameterized model. The parameterized deterministic traffic model defines a traffic constraint function that bounds the Source we list of most common of them here. The model should have a traffic constraint function that is as tight as possible so that the admission control algorithms do not overestimate the resources required by the connection. While, in general, a model with more parameters can achieve a more accurate traffic constraint function, the additional parameterization causes an increase in the complexity of poking the traffic model. Thus, the selection of an appropriate traffic model for a deterministic service must find a compromise between the high accuracy preferred by the admission control tests and the simplicity required for the implementation of traffic policers. The policing mechanisms must verify in real-time whether the traffic transmitted on an established connection adheres to a specified set of parameters of a deterministic traffic model. To ensure that the policing mechanisms can monitor and control traffic at high data rates, the complexity of the traffic model is limited. In [36], it was shown that a traffic model with a piece-wise linear concave traffic constraint function can be policed by a fixed number of leaky buckets. Since a leaky bucket can be implemented with a counter and a single timer [I5], concavity of the model's traffic constraint functions ensures a simple implementation of the traffic policer here we give the prosperities of the deterministic traffic model and then a short view of common deterministic traffic model.

(X_{min}, X_{av}, I, S_{max}) Deterministic Traffic Model [39]

Is proposed for providing real time service over real time channel where clients declare their traffic characteristics and performance requirement at the time of channel establishment in this model. It characterizes the traffic (offered load) by the minimum packet interarrival time on the channel X_{min} the minimum value, X_{av} of the average packet interarrival time over an interval of duration I,s maximum packet size Smax and the maximum service time t in the node for the channel's packets. For the performance bounds, the source-to-destination delay bound (or bounds) for the channel's packets, and the maximum loss rate. Note that X_{av} is the average interarrival time during the channel's busiest interval of duration I. Note also that specifying X_{min} and X_{av} together with S_{max} corresponds to requesting that the network provide a certain peak bandwidth and a certain long-term average bandwidth, respectively. If the channel request is accepted, i.e., if the desired bandwidths are allocated to the channel, the client is expected to satisfy by the offered load parameters, whereas the delay bounds are to be guaranteed by the provider, i.e., by the network. A traffic constraint function

$$A^*(t) = \left\lfloor \frac{t}{I} \right\rfloor \cdot \frac{I \cdot s}{x_{ave}} + \min\left\{ \left\lceil \left(\frac{t}{I} - \left\lfloor \frac{t}{I} \right\rfloor\right) \cdot \frac{I}{x_{min}} \right\rceil, \frac{I}{x_{ave}} \right\} \cdot s$$

2.1.2 Stochastic Bound Traffic Models

In this model the traffic generated by a source , i ,is said to be bounded over an interval of time of length t by a discrete random variable ,R_t. If R_t is stochastically larger than a random variable ,x is said to be stochastically larger than a random variable ,y, (denoted by X ≥ st Y). If and only if prob(X>x) ≥prob(Y>x) for all x. A source can bounded by different random variable, each of which bounds the source over a different length of time as the characterization of the source. In [12], is the first bounding stochastic model. It is proposed for computing upper bounds on the distribution of individual per session performance measures such as delay and buffer occupancy for networks in which sessions may be routed over several hops. Other stochastic bounds traffic modeled are proposed in [13] [16].

2.1.3 BIND Traffic Model

In[39], a deterministic traffic model(x_{min},x_{av},I,s_{max}) is proposed ,the author in [20] proposed the extension of this deterministic model to a probabilistic model within kurose's framework[12] ,further he extended kurose's model to make bounding random variables explicit functions of the interval length (BIND)in order to better characterize the properties of the source there are two general requirements for the stochastic BIND model:

$$R_t + R_s \geq_{st} R_{t+s}$$
$$E(R_t)\backslash t \leq E(R_s)/s \quad ,\text{if } t>s$$

Where R is a random variable stochastically bounds the total number of packets that can arrive on connection during any interval and E[R] is the mean bounding rate over any interval. The first property is stochastic subadditivity. The second property requires that the mean bounding rate over smaller time intervals is greater than the mean bounding rate over large time intervals. The author in [8] gave two examples of bounding model the first with discrete random variables and the second with continuous random variable . In discrete example the author used binomial random variables to bound the number of packets that can be generated by a source in intervals of different length. by choosing different parameters for each of the family's random variables, it is possible to bound different processes with complicated distribution. For the family of binomial bounding random variables let the j source denoted by S be described by {(R_{t},j,t), t≥0} where R_t stochastically bounds the total number of packets that can arrive on connection j during any interval of length t. the binomial distribution parameters is M_t and P_t which is given by the following equations:

$$R_t = \int_0^t \left\{ r_{1,t,1}(\textstyle\sum_\tau = 1) + r_{2,t,1}(\textstyle\sum_\tau = 2) \right\} d\tau$$
,
$$p_t = \left\{ \begin{matrix} c((\lambda_{pk} - \lambda_{pk})e^{-\gamma t/I} + \lambda_{av} - \lambda_{pk}e^{-\gamma}) \\ \end{matrix} \right\} T \leq t \leq I$$

$$p_t = \{\lambda_{av} / \lambda_{pk}\} t > I$$

Where $c = 1/(\lambda_{pk}(1-e^{-\gamma}))$ and γ ≥0 is a client specified parameter that controls how rapidly how rapidly the mean bounding rate over an interval approaches the long term average rate λ_{av} as the interval gets larger. A larger γ means that the speed with which λ_{av} is approached is faster. This is illustrated in figure 1.1 for I=133 ms .the figure show the mean bounding rate over {E(R_t)/t= M_tP_t/t} vs. interval length t for various values of γ. In the figure 1.2 we show the effect of the peak rate (burstiness) on the mean bounding rate. It shows that if two connections have the same long term average rate λ_{av} (with interval length no less than I), the mean bounding rate over any interval is greater for the connection with the higher peak rate λ_{pk} .the same property hold in the deterministic model with a fixed λ_{av} , a larger λ_{pk} means burstier traffic.

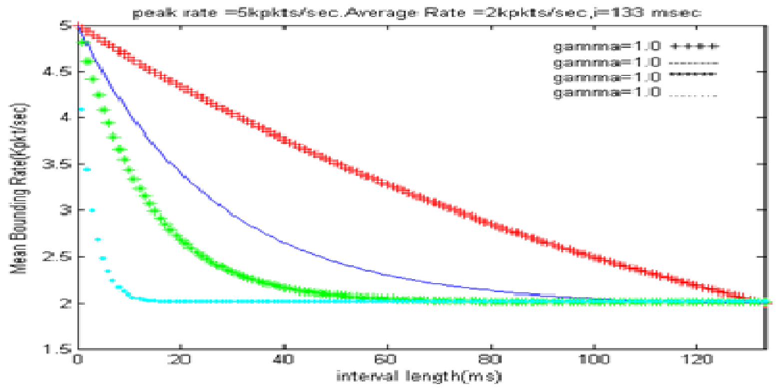

FIGURE 1.1

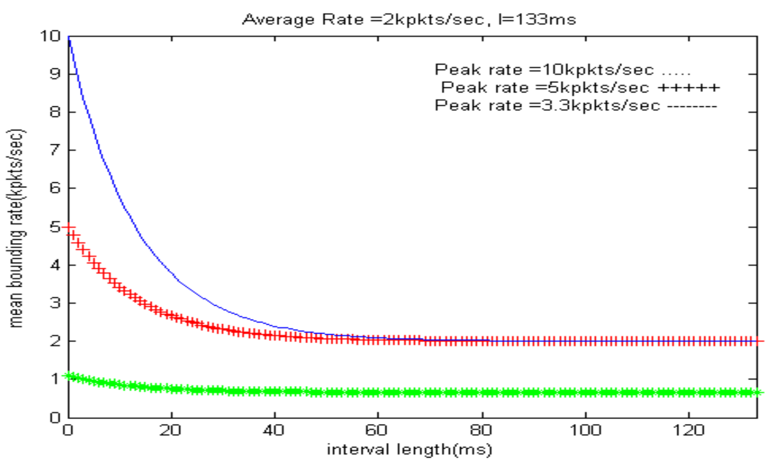

FIGURE 1.2

There are some researchers developed the BIND traffic model to overcome the multiplexing problem and low utilization. One of them extended this model with deterministic model [40] called (D-BIND) which can achieve 15-30% utilization with delay bound 30 ms. Other one introduced in [16] called (H-BIND) which achieve average utilization up to 86% , recently the author in [41] presented a(S-BIND) traffic model to on-line traffic. By using the S-BIND as input, Gamma H-BIND algorithm can achieve the maximum valid network utilization higher than the achievable network utilization under D-BIND traffic for both low-bursty and high-bursty on-line traffic, which is 50%~70 % model

2.2 Unbound (exact) Source Models

Unbound (exact) source models characterize source behavior by describing their stochastic properties through suitable distribution function and this category is divided into many subcategory, we describe each here.

2.2.1 Poisson Distribution Model

One of the most widely used and oldest traffic models is the Poisson Model. The memoryless Poisson distribution is the predominant model used for analyzing traffic in traditional telephony networks [2]. The Poisson process is characterized as a renewal process. In a Poisson process the inter-arrival times are exponentially distributed with a rate parameter µ: $p\{A_n \le t\} = 1-\exp(-\mu t)$. The Poisson distribution is appropriate if the arrivals are from a large number of independent sources, referred to as Poisson sources. The distribution has a mean and variance equal to the parameter µ. The Poisson distribution can be visualized as a limiting form of the binomial distribution, and is also used widely in queuing models. There are a number of interesting mathematical properties exhibited by Poisson processes. Primarily, superposition of independent Poisson processes results in a new Poisson process whose rate is the sum of the rates of the independent Poisson processes. Further, the independent increment property renders a Poisson process memoryless. Poisson processes are common in traffic applications scenarios that comprise of a large number of independent traffic streams. The reason behind the usage stems from Palm's Theorem which states that under suitable conditions, such large number of independent multiplexed streams approach a Poisson process as the number of processes grows, but the individual rates decrease in order to keep the aggregate rate constant. Nevertheless, it is to be noted that traffic aggregation need not always result in a Poisson process. The two primary assumptions that the Poisson model makes are:

1. The number of sources is infinite
2. The traffic arrival pattern is random.

The probability distribution function and density function of the model are given as:

$$F(t) = 1 - \exp(-\mu t)$$
$$f(t) = \mu \exp(-\mu t)$$

There are also other variations of the Poisson distributed process that are widely used. There are for example, the Homogeneous Poisson process and Non-Homogeneous Poisson process that are used to represent traffic characteristics. An interesting observation in case of Poisson models is that as the mean increases, the properties of the Poisson distribution approach those of the normal distribution.

2.2.2 Pareto Distribution Process

The Pareto distribution process produces independent and identically distributed (IID) inter-arrival times [1]. In general if X is a random variable with a Pareto distribution, then the probability that X is greater than some number x is given by

$$P(X > x) = (x / x_m)^{-k} \quad \text{For all } x \ge x_m$$

Where k is a positive parameter and x_m is the minimum possible value of X_i ,The probability distribution and the density functions are represented as

$$F(t) = 1 - (\alpha / t)^{\beta} \quad where \ \alpha, \beta \ge 0 \ \& \ t \ge \alpha$$
$$f(t) = \beta \alpha^{\beta} t^{-\beta - 1}$$

The parameters ß and α are the shape and location parameters, respectively. The Pareto distribution is applied to model self-similar arrival in packet traffic. It is also referred to as double exponential, power law distribution. Other important characteristics of the model are that the Pareto distribution has infinite variance, when ß≥ 2 and achieves infinite mean, when ß ≤ 1.

2.2.3 Markov Modulated Poisson Process

Markov models attempt to model the activities of a traffic source on a network, by a finite number of states. The accuracy of the model increases linearly with the number of states used in the model. However, the complexity of the model also increases proportionally with increasing number of states. An important aspect of the Markov model - the Markov property- states that the next (future) state depends only on the current state. In other words the probability of the next state, denoted by some random variable X_{n+1}, depends only on the current state, indicated by X_n, and not on any other state X_i, where $i<n$. The set of random variables referring to different states {X} is referred to as a Discrete Markov Chain. If the state transitions of the system under study happens only at integral values 0,1,2,3...n, then the Markov chain (MC) is discrete time and the random variable X follows a geometric distribution; otherwise, it is continuous time, with the random variable taking an exponential distribution. In a simple Markov traffic model, each of the state transition represents a new arrival process on the network. For modeling a continuous time system, the inter-arrival times are A Semi-Markov model is one that is obtained by allowing the time between state transitions to follow an arbitrary probability distribution. The time distribution between state transitions can also be ignored. In this model, the state transitions are then modeled as discontinuous entities with respect to time. The MC developed under such an assumption, is also referred to as an embedded or discrete Markov chain. Traffic models based on MMPP have been used to model bursty traffic. Due to its Markovian structure together with its versatility, the MMPP can capture bursty traffic statistics better than the Poisson process and still be amenable to queuing analysis. The simplest MMPP model is MMPP(2) with only four parameters: λo ,λ1 ,δo and δ1 Queuing models involving MMPP input have been analyzed in the 70s and 80s using Z-transform [26, 27, 28, 29]. Neuts developed matrix methods to analyze such queues [34]. For applications of these matrix methods for Queuing models involving MMPP and the use of MPP in traffic modeling and its related parameter fitting of MMPP the reader is referred to [30, 31, 32, 33]

2.2.4 Markov Modulated Fluid Models

Fluid flow models are conceptually simple. For instance, event simulation for an ATM multiplexer has several advantages, when fluid flow models are used for the simulation. Models other than the fluid flow models that distinguish between the cells and consider the arrival of each cell as a separate event, typically consume huge amounts of memory and CPU time for the simulation. On the contrary, a fluid flow model that characterizes the incoming cells by a finite flow rate, require comparatively less resources [1]. This is because in a fluid flow model, an event is generated only when the flow rate changes; and changes in flow rates are less frequent compared to the arrivals of cells. A fluid flow model as a consequence, utilizes lesser computing power and memory resources, compared to simulation using other models.The basic feature of a fluid model is to characterize the traffic on a network as a continuous stream of input with a finite flow/stream rate. In other words, the incoming traffic rate is represented as a stream with a finite rate. By capturing the rate changes at the input, the models analyze the different events that occur in the network. Because of the simple method of characterization of traffic, the fluid modes are analytically tractable and easier to simulate. Like any other Markov modulated process the Markov Modulated Fluid Model (MMFM), uses an underlying MC that determines the rate of the sources. At any instant, the current state of the underlying MC determines the flow rate of the inputs.

2.2.5 Autoregressive Models

The Autoregressive model is one of a group of linear prediction formulas that attempt to predict an output y_n of a system based on previous set of outputs $\{y_k\}$ where $k < n$ and inputs x_n and $\{x_k\}$ where $k < n$. There exist minor changes in the way the predictions are computed based on which, Several variations of the model are developed. Basically, when the model depends only on the previous outputs of the system, it is referred to as an auto-regressive model. It is referred to as a Moving Average Model (MAM), if it depends on only the inputs to the system [1]. Finally, Autoregressive-Moving Average models are those that depend both on the inputs and the outputs, for prediction of current output.Autoregressive model of order p, denoted as AR(p), has the following form

$$Xt = R1Xt-1 + R2Xt-2 + ... + RpXt-p + Wt$$

where W_t is the white noise, R_i are real numbers and X_t are prescribed correlated random numbers. The auto-correlation function of the AR(p) process consists of damped sine waves depending on whether the roots (solutions) of the model are real or imaginary. Discrete Autoregressive Model of order p, denoted as DAR(p), generates a stationary sequence of discrete random variables with a probability distribution and with an auto-correlation structure similar to that of the Autoregressive model of order p

2.2.6 Wavelet-based Models

These models use wavelet transform function to model long-rang dependence(LRD) traffic such as traffic measured on Ethernet. Note that long-rang dependence refers to degree of dependence of samples taken at one time on those taken at an earlier time. This dependence is measured by the autocorrelation function. Long-rang dependence (LRD) traffic has its autocorrelation function slowly decrease with time .anew multi scale tool for synthesis of non Gaussian LRD traffic called multifractal wavelet model (MWM) is presented in [10]. In [10], a sequence of the hear scaling coefficients and wavelet coefficients of different scale are recursively computed. Finally synthesis traffic in the time domain is reproduced. The study shows that the correlation structure of traffic is not the only factor on queuing network, but marginal and higher order moments of traffic captured by the MWM also have a tremendous impact on the queuing traffic behavior. In [9], an estimator of the Hurst parameter H from wavelet analysis is introduced

2.2.7 Traffic Models Using Chaotic Maps

Chaotic maps are low dimensional nonlinear systems whose time evolution is described by knowledge of an initial state and a set of dynamical laws. The chaos (irregular or seemingly stochastic behavior) exhibited by such systems arises from a property known as Sensitive dependence on Initial Conditions (SIC). In [5], the author illustrates traffic characteristics that can be modeled by considering several sample maps such The Intermittency map, Piecewise Linear Maps, The Intermittency map can be heavy tailed interarrival time densities, 1/f Noise, Fractal Dimensions, here we describe Piecewise Linear Maps in details.

Piecewise Linear Maps

As the name implies, for this class of maps f(.) consists of a number of piecewise linear segments. The Bernoulli Shift is a particularly simple example, and is defined as follows:

$$X n + 1 = \begin{pmatrix} x n \setminus d \ldots\ldots\ldots\ldots 0 \prec x n \le d \\ x n - d / 1 - d \ldots\ldots d \prec x n \prec 1 \end{pmatrix}$$

The associated indicator variable y_n, representing the packet generation process, is as before equal to 1 when x_n exceeds the threshold d, and is 0 otherwise. It is shown in [7] that the invariant density for this map is uniform and with every iteration, it generates a packet with probability with the arrivals forming an independent, identically distributed process. It follows that the active and passive periods are geometrically distributed.Burstier arrivals can be generated using additional piecewise linear segments. For example, it is shown in [7,8] that a three segment, two parameter map can generate a discrete analog of the Interrupted Poisson Process. More generally, it is shown in [7] that one can generate geometrically distributed dwell times in any segment by using piecewise linear segments with a uniform reinjection probability. One can then view this combination as a building block of geometrically distributed dwell times, analogous to the notion of an exponential stage in phase type processes. While it would be interesting to pursue this analogy, and investigate ways of combining piecewise linear segments, the chaotic map formulation may not offer any particular advantages in this regard. The real power of the chaotic map approach may lie in using nonlinear segments, which is illustrated next. In [9] the author use time Bernoulli Shift map to generate 100 second packet traffic by using chaotic map, Bernoulli shift map. And the characteristics of packet traffic such as packet rate, HURST exponent and Lyapunov characteristic exponent can be adjusted by the parameters of the Bernoulli shift map.

2.2.8 N- BURST TRAFFIC MODEL

The N-Burst introduced in [21][23] is a variant of the many ON/OFF models described in literature. The N-Burst arrival processes superposition of traffic streams from N independent, identical sources of ON/OFF type during its ON-time each source generates packets at rate λ_b and is quiet during its OFF time. This arrival process, with arbitrary ON and OFF time distributions (having Matrix-Exponential (ME) representations, see [19]) is analytically modeled as a Semi-Markov process of the Markov Modulated (MMPP) type. The details of this model Poisson Process can be found in [21] and [23]. When using Power-Tail Distributions for the duration of the ON periods, self-similar properties, which are critical for understanding teletraffic. Accommodating both burstiness and self-similarity in an analytic point-process model is not easy, and thus many approximations have been used by various researchers to understand buffer overflow problems and packet delay Some examples include the M/G/1 queue where the service time has infinite variance [15], continuous flow models during bursts [17, 25], and batch arrivals. The burst models are also known as ON-OFF models. For very low intra burst packet rates, the N-Burst/G/l model reduces to an M/G/l queue. For $\lambda_b \rightarrow \infty$ all packets in a burst arrive simultaneously and the model becomes a Bulk arrival, or M(X)/G/l, queue. In. the same limit, the packet-based model can be compared to a model on the burst level, an M/G/l queue where the individual customers represent complete bursts rather than individual packets. Thus the for the last mean system time describes the mean delay packet in a burst rather than the average over all packets The continuous flow model is also shown to be a limiting case of the N-Burst model by letting the number of packets in a burst n, and the router's packet service rate, v, go to infinity while holding their ratio constant. The author in [11] gave Numerical results comparing the steady-state results for Mean Packet Delay (mPD) and for Buffer Over flow Probabilities (BOP) of the different analytic models. They collectively show the critical importance of the Burstiness Parameter (the fraction of time that a source is OFF). The self similar N-burst /M/1 shows drastically changing steady-state performance for specific values of the Burstiness Parameter. The limiting models are incapable of describing the detailed structure of the performance in this transition region. In [11] the author defines the model by these parameters:

K: = the mean rate for each source (the average for ON- and OFF-times together),
λ := Overall arrival rate (packets per time unit)that generated by N-source
Where λ =KN
n_p: = Mean number of packets during a burst;
λ_p:= peak transmission rate during a burst (packets per time unit);
ON: =n_p/λ_p =Mean ON time for a burst (time units);
OFF: = Mean OFF time between bursts (time units);
v := Mean packet service rate of router (packets per Time unit);
$\lambda_b := \lambda/n_p$= Mean burst arrival rate (bursts per time unit);
$v_b := v/n_p$ = Mean burst service rate (bursts per time unit);
$x_b := n_p/v = 1/v_b$= Mean time to service a burst (time unit);
$\rho := \lambda/v$=router utilization

In addition, the author introduce the Burstiness Parameter, b, defined as

$$b = \frac{off}{off + on} = 1 - \frac{k}{\lambda_p}$$

This parameter can be thought of as a shape parameter, since
λ, or the amount of data sent per unit time, and ρ can be held constant as b is varied over its range, [0, 1].

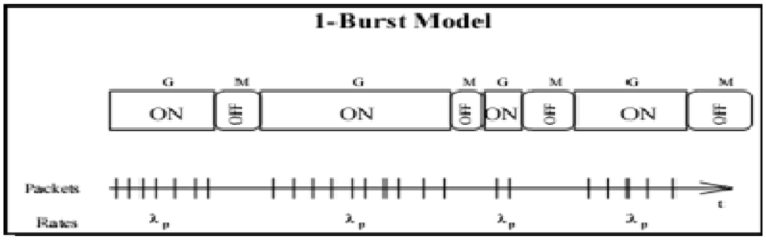

FIGURE 3: Diagram of 1-Burst traffic model

N-Burst model depends on four separate distributions, with random variables denoted by X_{SV}, X_{oF}, X_{ON} and X_{IN}, respectively. They are:

SV: Packet Service Time Distribution with mean1/v (distribution depends on packet-size distribution, service rate v depends upon router speed and size of packets)

OFF: OFF-Time distribution with mean OFF (depends on how bursts are generated, and how often);

ON: ON-Time distribution with mean ON causing a mean number of $n_p=\lambda_p$ ON a packets in a burst (e.g. . . ON-Time distribution depends on file size distribution, n_p depends on mean size of files, and on packet size);

IN: Inter-packet Time Distribution during a burst, with mean l/ λ_p.

Recall that for b = 0 the SM /M /l queue reduces to the $M_\lambda/M_v/l$ queue, in which case, the mean packet delay is given by the elementary formula:

$$\text{mPD(b=0)} = \left(\frac{1/v}{1-\rho}\right)$$

Where $\rho = \lambda / \nu$ *. At the other extreme (b = 1) is the bulk arrival* $M_{\lambda b}^{[ON]}$ */ Mv /l queue. This behavior is also well known (see, [9]), and can be written as:*

$$\text{mPD(b=1)} = \left(D\frac{1/v}{1-\rho}\right)$$

Where

$$D = \left(\frac{E\left(\frac{L(L+1)}{2}\right)}{E(L)}\right)$$

3. CONSLUSION

The different traffic models each have its own advantages and disadvantages and each can be suitable for special or general type of network .consequently, the type of network under study and the traffic characteristics strictly influence the choice of the traffic model used for analysis. Traffic models that cannot capture or describe the statistical characteristics of the actual traffic on the network are to be avoided, since the choice of such models will result in under-estimation or over-estimation of network performance. There is no one single model that can be used effectively for modeling traffic in all kinds of networks. For heavy-tailed traffic, it can be shown that Poisson model under-estimates the traffic [37]. In case of high speed networks with unexpected demand on packet transfers, Pareto based traffic models are excellent candidates since the model takes into the consideration the long-term correlation in packet arrival times[1].Similarly, with Markov models, though they are mathematically tractable, they fail to fit actual traffic of high-speed networks. All this model traffic describes by a random process such Poisson process or other have the following limitation:

- model fitting some sources cannot fit the model (no analytical model then no statistical guarantee can be made)

- homogeneous traffic sources and this not suitable for various service provide by network(mean heterogeneous source)
- need per connection analysis to provide different service to different application (don't take the effect of network element)
- limiting result
- single switch analysis
- at last stochastic process traffic models is suitable to characterize the one type data or for network that support one type of traffic
- does not scale the bursty traffic properly

The bound traffic models solve a lot of problem of stochastic process traffic model. bound traffic models are a good model to achieve hard QOS in real time application on the account of resource utilization in case of internet traffic the chaotic traffic model may be a good model since it describe the traffic self similarity characteristic and chaotic characteristic in a packet level .but this model does not capture the bursty characteristic well .it shown that N-BURST traffic model is general traffic model where model traffic in a burst level rather than all model where the individual customers represent complete bursts rather than individual packets, Accommodate self similar ,bursty, and long rang dependency property for the traffic, Can describe the performance of the system under various critical points, and describe various application with it's rich parameters (λ , λ_p , v , ON , OFF ,….e.g.).as mention above we can see many traffic models as special case of N-BURST model ($b \rightarrow 0, b \rightarrow 1$).A number of factors come into play while evaluating the efficiency of a traffic model. In general, the factor that differentiates one model from the other is the ability to model various correlation patterns and marginal distributions. Traffic models should have a manageable number of parameters, and parameter estimation should be simple; and, models that are not analytically tractable are preferred only for generating traffic traces.

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