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Stochastic Estimation of Wireless Traffic Parameters

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***Abstract*—**Different services based on different switching techniques in wireless networks leads to drastic changes in the properties of network traffic. Because of these diversities in services, network traffic is expected to undergo qualitative and quantitative variations. Hence, assumption of traffic characteristics and the prediction of network events become more complex for the wireless networks. In this paper, the traffic characteristics have been studied by collecting traces from the mobile switching centre (MSC). The traces include initiation and termination time, originating node, home station id, foreign station id. Traffic parameters namely, call inter-arrival and holding times were estimated statistically. The results show that call inter-arrival and distribution time in this wireless network is heavy-tailed and follow gamma distributions. They are asymptotically long-range dependent. It is also found that the call holding times are best fitted with lognormal distribution. Based on these observations, an analytical model for performance estimation is also proposed.

***Keywords*—**Wireless networks, traffic analysis, long-range dependence, heavy-tailed distribution.

I. INTRODUCTION

WIRELESS technology is advancing at a very fast rate and mobile phone has emerged as the primary mode of personal communication for convenience and ease of use with anywhere anytime anytype service. Mobile devices with multiple features are widely used all over the world for all personal communications services such as voice and data services. This has fuelled in an exponential increase of service demands through wireless networks. To cater the ever growing the demand, the mobile network service providers are facing the challenges of efficiently using the available resources. In wireless networks, the bandwidth, i.e. radio spectrum availability for initiating communications is the main concern. In addition, because of its support to mobility and roaming, the bit rate presently supported is limited where as the demand for the same is high. The next generation wireless networks will face the challenges to combine existing heterogeneous networks for high speed mobile communications with multiple services.

Therefore, traffic engineering is an important design tool to support different applications with different service requirements. To achieve optimum performance, designers and engineers must devise efficient techniques for mobility as well as resource management to meet next generation demands. It is important to understand the properties of wireless network traffic, to predict and to manage mobility [1] [2] for designing an efficient and robust wireless network. Data traffic was used for developing dynamic access of channels by analysing traffic data in an urban area. [3], [4]. The traffic capacity of code-division multiple access (CDMA) networks was predicted by modelling each cell as an independent Markov queue and the number of users in each cell as an independent random Poisson process. [5] In [6], the author presented the user-behaviour in a high speed packet access (HSPA) network. Empirical analysis of collected traffic traces have indicated the presence of self similarity in wired network traffic [7]-[9]. Multiclass Ethernet traffic shows long range dependencies over a period of time [9], [10]. This is to be contrasted with telephonic traffic which follows Poisson distribution in its arrival and Exponential distribution in departure. In traditional Poisson traffic [11], the short-term fluctuations are average out and come out with a constant mean value, when it is integrated over a longer time. The presence of multi-class traffic in wireless networks brings it closer to the wired networks and does not guarantee to behave the traditional way it is modelled for [12]-[15]. Multimedia applications, messaging, internet applications, e-commerce etc., may cause the traffic to show self-similarity like wired networks [10]. Hence, many of the previous assumptions, upon which wireless systems have been designed, may no longer be valid in the presence of self-similar traffic [16].

To analyse the network performance and to optimize the resource utilization, efficient modelling of the network traffic is of prime importance [17]. Most of the works in wireless networks has been done for voice traffic in circuit-switch multiplex network using Erlang B and C models. The Erlang models are based on the assumptions that the calls are independent identically distributed (iid) with Poisson arrival and exponential call holding time [18]. Now-a-days, multiple flow types are found in wireless network traffic which means its characteristics are not exactly the same as that of circuit-switched telephone traffic. Hence, the assumptions of Poisson arrival and exponential departure do not hold true for wireless traffic [16], [19]-[21]. Therefore, Erlang model may not estimate the actual blocking probabilities of the wireless traffic. Efforts have been made, to characterize wireless traffic based on measurements specially, for estimating the impact of emerging popular applications [16], [17], [20]-[24].

In this work, raw network data traces were collected from a wireless network from service provider's MSC. The collected data contains raw data of traffic events occurring among mobile phones and base stations. Various characteristics of this large collection of data were analysed to determine call Inter-arrival times distribution and call holding time

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distribution. The self-similar nature of the traffic is also tested. To summarize, the current work describes a novel approach of designing the wireless networks through analysis of the actual traffic data, collected from the MSC of a wireless network that supports multiple services. Based on the observations, an analytical model for performance measures of wireless network is also proposed.

Rest of the paper is organised as: Section II describes data collection, Section III deals with the statistical analysis of the data, Section IV discuss the results of the data analysis and performance model, Section V concludes the paper.

II. Data Collection

The analysed data were collected from a wireless backbone which provides services like messaging, web chatting, video streaming, e-mail, internet browsing, video/audio downloading, from a service provider. It supports packet data speeds of up to 307 kbps in a single 1.25 MHz channel, up to 40 simultaneous voice calls per single 1.25 MHz FDD channel, Short Messaging Service (SMS), Multimedia Messaging Service (MMS), MMS enable graphics, pictures, video or music to be attached to text messages and sent to mobile devices or computers, music and video downloads. The collected traffic trace contains call arrival time, departure time, packet size, dropped call, call originating node, home station ID, foreign station ID (Care-of-Address). Table I presents the average trace data of 8 busiest hours used for analysis in this work.

TABLE I
Average Trace Data of 8 Busiest Hours

Time	Total Calls	Average Calls/Sec
1st Hour	29,885	0.35
2nd Hour	26,276	0.41
3rd Hour	25,013	0.34
4th Hour	16,142	0.42
5th Hour	18,345	0.30
6th Hour	20,658	0.28
7th Hour	25,439	0.22
8th Hour	30,732	0.21

III. Statistical Analysis

A. Self-Similarity, Long-Range Dependence and Heavy Tailed Distributions

In this paper, the determination of presence of Self Similarity and long-range dependence in wireless traffic is stressed by estimating the Hurst Parameter and heavy-tailedness of the traffic distributions [16]. The Hurst parameter [25] H is a measure of the level of self-similarity of a time series and its long-range dependence.

Let $X = \{X_t : t = 0, 1, 2, 3, \ldots\}$ represent the stochastic [26] stationary packet arrival process with mean $\mu = E(X_t)$, variance $\sigma^2 = Var(X_t)$ and autocorrelation function (ACF)

$$R(k) = \frac{E[(X_t - \mu)(X_{t+k} - \mu)]}{\sigma^2},$$

where $k = 0, 1, 2, \ldots$ and represents the time lag of the process. X_t represents the call arrivals at the t^{th} time slot of 10 ms each. If the whole sample size is divided into non-overlapping blocks of size $m = 1, 2, 3, \ldots$, then the new stationary time series

$$X^{(m)} = \{X_k^{(m)} : k = 1, 2, 3, \ldots\}$$

can be obtained by averaging the original data series X.

For each $m = 1, 2, 3, \ldots$, the series $x_k^{(m)}$ can be expressed as

$$x_k^{(m)} = \frac{1}{m}(x_{km-m+1} + \ldots + x_{km}), \quad k \geq 1$$

This represents the same stationary stochastic process [26] as X with mean $\mu = E(X^{(m)})$, variance

$$Var(X^{(m)}) = \frac{\sigma^2}{m} + \frac{2\sigma^2}{m^2}(m-k)\,R(k),$$

Autocorrelation

$$R^{(m)}(k) = \frac{\sigma^2}{m^2\,Var(X^m)}\left\{mR(m.k) + 2\sum_{j=1}^{m-1}(m-j)R(m.k+j)\right\}$$

Now, both the series $X^{(m)}$ and X will have the equal Self-Similar [10] nature when equations

a) $R^{(m)}(k) = R(k)$ and b) $Var(X^{(m)}) = \sigma^2 m^{-\beta}$

are satisfied. For large m which is the case for network traffic analysis, the process is said to be asymptotically Self-Similar and is defined as

$$Var(X^{(m)}) = cm^{-\beta},$$

where c is constant, $m \to \infty$.

It shows that the variance of the sample mean decreases more slowly the reciprocal of the sample size m that implies $\sum_{k=0}^{\infty} R(k) = \infty$. The value of Hurst parameter can be calculated as $H = 1 - \beta/2$. It can also be calculated from

$$R^{(m)}(k) \cong \frac{1}{2}\left((k+1)^{2H} - 2k^{2H} + (k-1)^{2H}\right), m \to \infty.$$

For a second-order stationary process to be Long-range dependence [24], the value of H should between 0.5 and 1. A value of 0.5 indicates the absence of self-similarity and the value closer to 1, the greater the degree of long-range dependence.

B. Goodness-of-Fit Test

All In most network analysis, the knowledge of underlying distribution is required and mostly it is assumed based on prior evidences. When the underlying distribution is not known or not dependable, it is important to have some type of test that can establish the "Goodness-of-Fit" between the postulated distribution type of random variable X and the evidence contained in the experimental observations. Graphical methods are generally used to determine goodness of fit. We'll use analytical methods.

In our case, X is a discrete random variable that represents the wireless network traffic data with unknown pmf given by $P\{X(i)\} = p_i$. Now, we'll test the null hypothesis that X possesses a certain specific pmf given by $p_i = p_{i_0}$, $0 \le i \le k-1$. Our goal then is to test H_0 against H_1, where:

$$H_0 : p_i = p_{i_0},\ i = 0, 1, 2, \ldots k-1,\ H_1 : not\ H_0$$

Now, let we have n observations and N_i be the observed number of times (out of n) that the measured value of X takes the value i. N_i is clearly a binomial [26] random variable with parameters n and p_i so that $E[N_i] = np_i$ and $Var[N_i] = np_i(1 - p_i)$. Therefore, the statistics

$$Q = \sum_{i=0}^{k-1} \frac{(N_i - np_i)^2}{np_i}$$

is chi-squire distribution [26] with $(k-1)$ degree of freedom and can be written as

$$\chi^2_{k-1} = \sum_{i=0}^{k-1} \frac{(observed - \exp ected)^2}{\exp ected}$$

here, X is a continuous random variable and the hypothesis test for the distribution of X is

$$H_0 : for\ all\ x,\ F_X(x) = F_0(x)$$

against

$$H_1 : there\ exists\ x\ such\ that\ F_X(x) \ne F_0(x)$$

The chi-squire test was applied here but image of X has to be divided into a finite number of categories and hence there will be a loss of power of the test. Therefore, Kolmogorov-Smirnov [20] test is preferred for continuous population distribution. In this test, the random samples are first arranged in order of magnitude so that the values are assumed to satisfy $x_1 \le x_2 \le x_3 \ldots \le x_n$. Then the empirical distribution function $\psi_n(x)$ is defined as:

$$\psi_n(x) = \begin{cases} 0, & x < x_1 \\ i/n, & x_i \le x \le x_{i+1} \\ 1, & x_n \le x \end{cases}$$

The alternative definition of $\psi_n(x)$ is:

$$\psi_n(x) = \frac{number\ of\ \ values\ in\ \ the\ \ sample\ that\ \ are \le x}{n}$$

A natural measure of deviation of the empirical distribution function from $F_0(x)$ is the absolute value of the difference:

$$d_n(x) = |\psi_n(x) - F_0(x)|$$

Since $F_0(x)$ is known, the deviation $d_n(x)$ can be calculated for each value of x. The largest of these values, as x varies over its full range, is an indicator of how well $\psi_n(x)$ approximates $F_0(x)$. As $\psi_n(x)$ is a step function with n steps and $F_0(x)$ is continuous and non-decreasing, it suffices to evaluate $d_n(x)$ at the left and right end points of the intervals $[x_i, x_{i+1}]$. Then, the maximum value of the $d_n(x)$ is the value of the Kolmogorov-Smirnov (K-S) estimator defined by:

$$d_n(x) = \sup_x |\psi_n(x) - F_0(x)|$$

We reject the null hypothesis at a level of significance α if the observed value of the statistic d_n exceeds the critical value $d_{n;\alpha}$, otherwise we rejects alternative hypothesis H_1.

IV. Analysis and Results

The traced data for call inter-arrival times and call holding times were analysed. The Kolmogorov-Smirnov [20] test were performed to determine the best fit distribution for each trace of call inter-arrival times and call holding times. Normal distribution, exponential, weibull, lognormal, gamma distributions were considered to determine the goodness-of-fit test. The parameters are estimated for call inter-arrival times with the maximum likelihood method [21] and are given in Table II. $h = 1$ indicates that the null hypothesis test is rejected when the Kolmogorov-Smirnov test parameter d is greater than critical value. $h = 0$ means the hypothesis for the distribution is accepted. Tests are performed with 90% confidence. p-value or descriptive level of a test is defined as the probability of getting a result as extreme as, or more extreme than, the observed result under null hypothesis i.e. the p-value of a test H_0 is the smallest level of significance a at which the observed test result would be declared significant or would declared indicative of rejection of H_0 .

We also calculated the autocorrelation function, tested self similarity and Long-range dependency of the traced traffic data.

TABLE II
K-S TEST RESULTS FOR CALL INTER-ARRIVAL TIMES

Distribution	Para meter	1st hour	2nd hour	3rd hour	4th hour
Normal	h	1	1	1	1
	p	0.0053	0.0047	0.0046	0.0038
	d	0.0282	0.0325	0.0252	0.0188
Exponential	h	1	1	1	0
	p	0.054	0.043	0.041	0.035
	d	0.0250	0.0281	0.0295	0.0311
Weibull	h	0	0	0	0
	p	0.422	0.401	0.382	0.324
	d	0.0150	0.0141	0.0137	0.0131
Gamma	h	0	0	0	0
	p	0.482	0.436	0.402	0.378
	d	0.0162	0.0147	0.0137	0.0128
Lognormal	h	1	1	1	1
	p	2.36e-20	1.88e-20	1.75e-20	1.59e-20
	d	0.0802	0.0824	0.0835	0.0857

A. Call Inter-Arrival Times

To determine the distribution of call inter-arrival pattern, Normal, exponential, Weibull, gamma, lognormal distribution were considered and found that except normal, other four distributions namely exponential, Weibull, gamma, lognormal fit the data better but only Weibull and Gamma distribution pass the significance test with 90% confidence for all hourly traces where as exponential pass hypothesis test only for two hourly traces. The higher p values of Weibull and Gamma distribution show better fit than exponential distribution. Non Poisson and different distribution is also reported by [25] and [20]. Call inter-arrival time distribution is shown in Fig. 1.

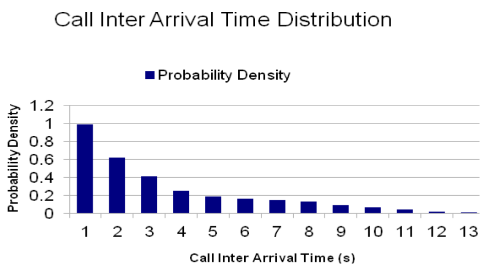

Fig. 1 Call inter-arrival distribution

The autocorrelation [26] coefficients of the call inter arrival times with different lags from the hourly traces are also determined with 95% and 99% confidence levels and they are shown in Table III. Most of the autocorrelation [26] coefficient values, computed with the lag values smaller than 60, are found to remain outside the range of the confidence intervals. This shows non negligible correlation among call inter-arrival times. The traces of call inter-arrival times were also tested for long range dependence by estimating the Hurst parameter. Estimates of H for hourly traces are shown in Table IV. For all the traces H is found to be greater than 0.5. This shows that call inter-arrival times exhibit long-range dependency and self-similarity

TABLE V
VALUE OF H FOR HOURLY TRACES OF CALL HOLDING TIMES

Lag	Coefficients
10	-0.036
20	0.017
30	0.043
40	0.041
50	-0.046
60	0.023
70	-0.032
80	-0.045
90	0.024
100	-0.036
110	-0.017
120	-0.030
130	-0.032

TABLE IV
H VALUE FOR CALL INTER-ARRIVAL TIMES

Hour	Value of H
1	0.832
2	0.921
3	0.850
4	0.901
5	0.846
6	0.887
7	0.919
8	0.827

B. Call Holding Times

We compare the distribution of the call holding times with the same procedure that were followed for the call inter-arrival times. The probability density function of the call holding times is shown in Fig. 2. None of the considered distributions namely Normal, Exponential, Weibull, Gamma, Lognormal passes the test when the traces are tested with 10% and 5% significance levels. Therefore, randomly chosen sub-traces of length 1,000 extracted from each hourly trace were used to test with a significance level α of 1%. This time only lognormal distribution passes the test for very few sub-traces. When sub-traces of length 500 are tested with the same significance level, the lognormal distribution [27], [21] exhibits the best fit. It passes the Kolmogorov-Smirnov (K-S) test for almost all 1000 sample sub-traces of all hourly traces. The test rejects the null hypothesis when those sub-traces are compared with the other four candidate distributions namely normal, exponential, Weibull, and gamma. Non Poisson and different distribution is also reported by [25], [27] and [20].

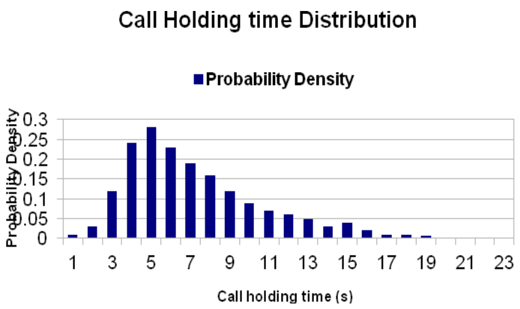

Fig. 2 Call holding times distribution

The autocorrelation coefficient of the call holding times from the hourly traces were determined as shown in Table V and found that there are no significant correlations for non-zero lags because all but a few autocorrelation coefficients are within the 95% and 99% confidence intervals. The long-range dependence in the call holding times is also investigated by calculating the Hurst parameter H as shown in Table VI. For all traces $H < 0.5$ showing that call holding times are not long-range dependent.

TABLE VI
H VALUE FOR CALL HOLDING TIMES

Hour	Value of H
1	0.472
2	0.478
3	0.458
4	0.456
5	0.483
6	0.473
7	0.465
8	0.486

C. Performance Measures for the QoS

Let us consider a wireless network with N sources of multiclass traffic that can be broadly categorized as elastic traffic and non-elastic traffic [15]. Voice call stream traffic is ON-OFF, non elastic and other traffics are elastic in nature. We have found that, in the presence of multiclass traffic, neither inter-arrival times nor call holding times are exponentially distributed [25], [27]. Therefore, to analyse the performance of a wireless network, we'll generalize the arrival process by removing the restriction of the exponential inter-event times. If X_i be the time between the i^{th} and the $(i-1)^{th}$ call arrivals, then $\{X_i \mid i = 1, 2, 3, \ldots\}$ will represent the sequence of independent identically distributed random variables and hence the process will constitute a renewal process [26]. Here, X_i represents a continuous random variable and let us assume that the underlying distribution of this renewal process is $F(x)$. If S_k represents the time from the beginning till the k^{th} call arrival, then

$$S_k = X_1 + X_2 + X_3 + \ldots + X_k \qquad (1)$$

and if $F^{(k)}(t)$ denotes the distribution function of S_k , clearly, $F^{(k)}$ is the **k**-fold convolution [20] of F with itself. For notional convenience, we define

$$F^{(0)}(t) = \begin{cases} 1, & t \geq 0 \\ 0, & t < 0 \end{cases} \qquad (2)$$

Our primary objective here is to determine the number of calls $N(t)$ in the interval $(0,t)$. $N(t)$ is a discrete parameter called renewal random variable here. Then, the process $\{N(t) \mid t \geq 0\}$ is a discrete-state, continuous-time renewal counting process [15]. Now, it can be observed that $N(t) = n$ if and only if $S_n \leq t \leq S_{n+1}$ Then,

$$\begin{aligned} P[N(t) = n] &= P(S_n \leq t \leq S_{n+1}) \\ &= P(S_n \leq t) - P(S_{n+1} \leq t \\ &= F^{(n)}(t) - F^{(n+1)}(t) \end{aligned} \qquad (3)$$

If $M(t)$ be the average number of call arrivals in the interval $(0,t)$, then

$$\begin{aligned} M(t) &= E[N(t)] = \sum_{n=0}^{\infty} nP[N(t) = n] \\ &= \sum_{n=0}^{\infty} nF^{(n)}(t) - \sum_{n=0}^{\infty} nF^{(n+1)}(t) \\ &= \sum_{n=0}^{\infty} nF^{(n)}(t) - \sum_{n=1}^{\infty} (n-1)F^{(n+1)}(t) \\ &= F(t) + \sum_{n=1}^{\infty} F^{(n+1)}(t) \end{aligned} \qquad (4)$$

It can be noted that $F^{(n+1)}$ is the convolution [20] of $F^{(n)}$ and F . Assuming f be the density function of F , it can be written as

$$F^{(n+1)}(t) = \int_0^t F^{(n)}(t-x)\, f(x)\, dx \qquad (5)$$

Therefore

$$\begin{aligned} M(t) &= F(t) + \sum_{n=1}^{\infty} \int_0^t F^{(n)}(t-x) f(x)\, dx \\ &= F(t) + \int_0^t \left[\sum_{n=1}^{\infty} F^{(n)}(t-x) \right] f(x)\, dx \\ &= F(t) + \int_0^t M(t-x)\, f(x)\, dx \end{aligned} \qquad (6)$$

The rate of average call arrivals $m(t)$ can be defined to be the derivative of $M(t)$, i.e.

$$m(t) = \frac{dM(t)}{dt} \qquad (7)$$

For small h, $m(t)h$ denotes the probability of a call arrival in the interval $(t, t+h)$. Thus for Poisson process, $m(t)$ equals the Possion rate λ. To determine $m(t)$, taking Laplace transform [26] on both sides and using convolution property of the transform, (7) can be rewritten as

$$L(m(t)) = L(f(t)) + L(m(t))L(f(t)) \tag{8}$$

Therefore,

$$L(m(t)) = \frac{L(f(t))}{1 - L(f(t))}$$

and

$$L(f(t)) = \frac{L(m(t))}{1 - L(m(t))} \tag{9}$$

i.e. if either $f(t)$ or $m(t)$ is known, the other can be determined. When $F^{(n)}(t)$ is a Gamma or n-stage Erlang distribution [20], then

$$F^{(n)}(t) = 1 - \left[\sum_{k=0}^{n-1} \frac{(\lambda t)^k}{k!}\right] e^{-\lambda t}$$

and hence from (3) one can write

$$P[N(t) = n] = F^{(n)}(t) - F^{(n+1)}(t) = \frac{(\lambda t)^n}{n!} e^{-\lambda t} \tag{10}$$

Thus $N(t)$ has a Poisson distribution [15] with parameter λt.

Now, let us assume that Call holding times are not exponential [20] and are independent general random variables with common distribution function G. If $X(t)$ is number of calls in the system at time t and $N(t)$ is the total number of call arrivals in the interval $(0, 1)$. The number of departures $D(t) = N(t) - X(t)$.

It is known that for $n \geq 1$ occurred arrivals in the interval $(0, t)$, the conditional joint pdf of the arrival times $T_1, T_2, T_3, \ldots T_n$ is given by [26]

$$f(t_1, t_2, t_3, \ldots, t_n \mid N(t) = n) = \frac{n!}{t^n} \tag{11}$$

When a call arrive at time $0 \leq y \leq t$, from **(**11**),** the time of arrival of the call is independently distributed on $(0, t)$ i.e.

$$f_Y(y) = \frac{1}{t}, \quad 0 < y < t$$

The probability that this call is still undergoing service at time t given that it arrived at time y is $1 - G(t-y)$. Then the unconditional probability that the call is undergoing service at time t is

$$\begin{aligned} p &= \int_0^t [1 - G(t-y)] f_Y(y)\, dy \\ &= \int_0^t \frac{1 - G(t-y)}{t} dy \\ &= \int_0^t \frac{1 - G(x)}{t} dx \end{aligned} \tag{12}$$

If n calls have arrived and each has the probability p of independently not completing by time t, then a sequence of n Bernoulli [26] trials is obtained. Thus,

$$P[X(t) = j \mid N(t) = n] = \begin{cases} {}^nC_j p^j (1-p)^{n-j}, & j = 0, 1, .. n \\ 0, & otherwise \end{cases}$$

Then by theorem of total probability [26]

$$\begin{aligned} P[X(t) = j] &= \sum_{n=j}^{\infty} {}^nC_j p^j (1-p)^{n-j} e^{\lambda t} \frac{(\lambda t)^n}{n!} \\ &= e^{-\lambda t} \frac{(\lambda tp)^j}{j!} \sum_{n=j}^{\infty} \frac{[\lambda t(1-p)]^{n-1}}{(n-j)!} \\ &= e^{-\lambda tp} \frac{(\lambda tp)^j}{j!} \end{aligned} \tag{13}$$

Thus, the number of calls in service in the system at the time t has the Poisson distribution with parameter

$$\lambda' = \lambda tp = \lambda \int_0^t [1 - G(x)]\, dx \tag{14}$$

when call holding times are exponentially distributed with parameter μ then $G(x) = 1 - e^{-\mu x}$

$$\int_0^t [1 - G(x)] dx = \frac{1}{\mu} - \frac{e^{-\mu t}}{\mu}$$

hence,

$$t \to \alpha, \; \lambda' = \frac{\lambda}{\mu}$$

Now, if the number of channels in a cellular wireless network system is C and the new calls are dropped when all channels are busy, then probability of drops can be calculated from (13) as

$$P[X(t) = C] = e^{-\lambda tp} \frac{(\lambda tp)^C}{C!} \tag{15}$$

as a special case, when C is finitely large and call inter arrivals and departures are both exponentially distributed, probability of drops from (14) for a steady state can be rewritten as

$$P[X(t)=C]=\frac{\frac{\rho^C}{C!}}{\sum_{i=0}^{C}\frac{\rho^i}{i!}}$$

where the denominator in the right is normalization factor and ρ is traffic intensity λ/μ, This is known as Erlang's B formula [25].

V. Conclusion

In this paper, we analyze the traffic data collected from wireless network with multiclass traffic. Our observation shows that call inter-arrival time distribution can be best modelled by both gamma (Erlang) as well as weibull distributions instead of exponential distribution. Incoming traffic displays the properties of self-similarity and long-range dependency, too. Call holding times distribution can be best expressed by lognormal distributions without showing long-range dependency. The non-Poisson arrivals and non-Exponential departure has also been reported in [25], [27]. Based on these observations, a model for estimating the probability of drops and it is shown that Erlang B formula can be derived from this as a special case. Therefore, Erlang B and C models, which are mostly used to shape traffic in circuit switched networks, does not always give optimum output for wireless networks with multiclass traffic, This study may be useful for designing next generation wireless networks.

References

[1] Samanta, R.K., Bhattacharya, P, and Sanyal, Gautam (Nov. 2008)"A Generic Model for Prediction of Mobility of Mobile Nodes in Cellular Networks", Int. Conf. on Advanced Computing & Communication Technologies, Panipat, India, , pp.410-414.

[2] Keshav, S (April 2005) "Why Cell Phones Will Dominate the Future Internet", ACM Computer Comm. Review, Vol. 35, No.2, pp. 83-86.

[3] Willkomm, D., Machiraju, S., Bolot, J., and Wolisz, A., (2009) “Primary user behavior in cellular networks and implications for dynamic spectrum access,” IEEE Communications Magazine, vol. 47, no. 3, pp. 88–95.

[4] Beyme, Steffen., Leung, Cyril., (2014) “A stochastic process model of the hop count distribution in wireless sensor networks”, Ad Hoc Networks 17 60–70 (Elsevier).

[5] Evans, J. S. , and Everitt, D., (1999)“On the teletraffic capacity of cdma cellular networks,” IEEE Transactions on Vehicular Technology, vol. 48, no. 1, pp. 153–165,.

[6] Laner, M., Svoboda, P., Schwarz, S. and Rupp, M. (2012) “Users in cells: a data traffic analysis,” IEEE Wireless Communications and Networking Conference (WCNC), pp. 3063–3068.

[7] Paul, U., Subramanian, A. P., Buddhikot, M. M., and Das, S. R. (2011) “Understanding traffic dynamics in cellular data networks,” Proceedings IEEE INFOCOM, pp. 882–890.

[8] Jain, R., and Routhier, S. (1986) "Packet trains-measurements and a new model for computer network traffic", IEEE J. Select. Areas Comm.., 4(6):986-995.

[9] Crovella, M. E. and Bestavros, A. (1997) “Self-Similarity in World Wide Web traffic: Evidence and possible causes.” IEEE/ACM Transactions on Networking 5, pp. 835-846.

[10] Leland, W.E., al., et, (Feb. 1994)"On the Self-Similar Traffic Nature of Ethernet Traffic", IEEE Trans. Networking, vol. 2, no. 1, , pp. 1-15.

[11] Bhattacharjee, P., and Sanyal, G. (April 2008) "Design Tool For An Edge Router Using Appropriate Mathematical Model", International Journal of Systemics, Cybernetics and Informatics.

[12] Adya, A., Bahl, P. and Qiu, L.(November 2001) "Analyzing Browse Patterns of Mobile Clients", Proceedings of ACM SIGCOMM Internet Measurement Workshop, San Francisco, CA, pp. 189-194.

[13] Adya, A., Bahl, P., *and* Qiu, L., (2002) "Characterizing Alert and Browse Services for Mobile Clients", Proceedings of USENIX Technical Conference, pp. 343-356.

[14] Tsybakov, B., (1999) "Probability of heavy traffic period in third generation CDMA mobile communication," Proceedings of IEEE Workshop on Mobile Multimedia Communications, MoMuC'99, pp. 27-34.

[15] Bhattachmjee, P., and Sanyal, G. (2008) "Congestion Control by Restricted Flow Admission in a Multi Class Network", Proceeding of lASTED conference (629), on Communication Systems and Networks- .

[16] Erramilli, A., Roughan, M., Veitch, D., and Willinger, W. (2002) "Self-similar traffic and network dynamics," Proceedings of the IEEE, vol. 90, no. 5,pp. 800-819.

[17] Mokdad, L., Ben-Othman, J., Yahya, B. and Niagne., S.(January, 2014) Performance evaluation tools for QoS MAC protocol for wireless sensor networks, Ad Hoc Networks archive, Volume 12, pp. 86-99, (Elsevier).

[18] Evans, J., and Everitt, D. (1999) "On the teletraffic capacity of CDMA cellular networks," IEEE Transactions on Vehicular Technology, vol. 48, pp. 153-165.

[19] Jeon, W. and Jeong, D. (October 2002) "Call Admission Control for CDMA Mobile Communications Systems Supporting Multimedia Services", IEEE Transactions on Wireless Communications, Vol. 1, No. 4, pp. 649- 659.

[20] Sanchez, J.I., Barcelo, F. and Jordon, J. (1998) "Inter-arrival time distribution for channel arrivals in cellular telephony", Proc. of the 5th Int. Workshop on Mobile Multimedia Comm. MoMuc'98, Berlin.

[21] Barcelo, F. and Jordon, J. (1998) "Channel holding time distribution in cellular telephony", Electronics Letters,Vol. 34, No.2, pp.l46-147,

[22] Kunz, T., Barry, T., Zhou, X., Black, J. and Mahoney, H. (August 2000) "WAP Traffic: Description and Comparison to WWW Traffic", Proceedings of ACM MSWiM, Boston, MA, pp. 11-19.

[23] Shankaranarayanan, N., Rastogi, A. and Jiang, Z. (April 2002) "Performance of a Wireless Data Network with Mixed Interactive User Workloads", Proceedings of IEEE International Conference on Communications (ICC), New York, NY,.

[24] Navaie, K., Sharafat, A.R. and Zhao, Y.Q. (2005) "On the Impact of Traffic Characteristics on Radio Resource Fluctuation in Multi-Service Cellular CDMA Networks", 0-7803-8887-9/05 © IEEE.

[25] Rajaratnam , M. and Takawira, F. (Sept. 2000) "Hand-Off Traffic Characterisation in Cellular Networks Under Non-Classical Arrival And Gamma Service Time Distributions" IEEE PIMRC 2000, pp. 1535-1539.

[26] Allen, A.O. (1978) "Probability, Statistics and Queuing Theory with Computer Science Applications", Academic Press, New York.

[27] Antoniou, I., Ivanov, Victor V., Ivanov, Valery V. , Kalinovsky, Yu. L. and Zrelovc, P. V. (2004) "On the log-normal distribution of network traffic", Discrete Dynamics in Nature and Society (1), Issue 1, pp. 19-34.