PERFORMANCE COMPARISON OF MODELS OF INDIVIDUAL AND MERGED BURSTY TRAFFICS

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1 Introduction

Traffic models are an essential component of performance analyses of telecommunication networks. Good models should be simple, accurate and applicable in both mathematical analysis and computer simulations.

In circuit switched networks, including narrowband ISDN, traffic is usually modelled as Poisson or characterised in terms of its first few moments. For packet switched networks, such as B-ISDN based on ATM, the Poisson model may still be applicable for some types of services on a higher level, such as call requests. However, when it comes to low level issues, for example dimensioning buffers in switches, a Poisson model is not likely to be valid. This is because most sources in such a network are known to produce information at a much more uneven rate than Poisson. Such traffic is commonly referred to as bursty, and it may even contain strong long term correlation. This has lead to the development of a large number of models emphasising different aspects of the packet arrival processes.

Strictly speaking, a complete model is not only the model itself but also a procedure to compute its parameters from some characteristic traffic data. It has been argued that different models and different traffic characteristics should be used for different sources [6]. Yet, to enable sufficiently general analysis and dimensioning of packet switched networks, it is most desirable to find characteristic parameters of traffics that are independent of sources, and tractable models that can reproduce these. Proposals for such a set of parameters, which we have not been able to verify as yet, are reported in [1, 23].

The present work, which is a part of a long term project, is an attempt to systematically collect and compare a number of commonly used models and fitting methods. Some earlier results are found in [3, 4]. Our approach is to apply all models/fitting methods to the same data and examine differences in their performance. Having computed model parameters from given data using different techniques, the models are run in a computer simulator. The simulator consists of a server with a deterministic service time and an infinite queue, the performance of which is recorded and analysed. When several arrival processes are run in parallel, these are independent. Since all models are fitted to reproduce the same traffic, differences in the performance of the single server system reflect differences between models.

The models and fitting methods used in the present work are reviewed in section 2. Due to space limitations, our review has been condensed and we refer to associated work and [5] for details. Section 3 is devoted to results, both for a single source and for multiple sources. Finally, we reach some limited conclusions and point to further work.

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2 Models and Fitting Methods

2.1 Estimation of Traffic Characteristics

The important characteristics of most models presented in the literature are average rate, peak rate and burst length, although these are often used without explicit definitions.

The average rate is possibly the only metric for which a proper definition is relatively straightforward. Denoting the number of arrivals during a time t by $N(t)$, the average rate $\overline{r}$ can be defined as

$$\overline{r} = \lim_{t\to\infty} \frac{N(t)}{t} \tag{1}$$

The peak rate can intuitively be defined as the inverse of the shortest interarrival time that a given source is capable of producing, but this can lead to an almost infinite peak rate which is not useful in practice. A possibly more appealing approach is to relate the two concepts of peak rate and burst to each other: peak rate is the transmission rate during a burst and a burst length is the period during which a source transmits at the peak rate. Although peak rates and burst lengths defined in this way may be given numbers for the purpose of a theoretical analysis, this definition is not sufficient to estimate the characteristics from real data: When does a burst actually begin and where does it end?

Throughout our work, we have adopted the definition of a burst used by Solé et al., [19, 20]: A burst consists of arrivals that are not separated by more than a maximum allowed interarrival gap (MAIG), in an appropriate time unit, and must last at least for $L_{\min}$ time units. The last arrival within a burst is separated from the next arrival by at least an interval of MAIG time units. Also, a sequence of arrivals, each separated by less than the MAIG, is not considered a burst unless the time from the first arrival to the last one is at least $L_{\min}$. Like [19, 20], we use the mean interarrival time $1/\overline{r}$ as both MAIG and $L_{\min}$, though other values could be used as well.

2.2 The Autoregressive Markov Model

The autoregressive Markov model (AMM), due to Maglaris et al. [12], generates a Markov dependent number of arrivals within a frame. Denoting the number of arrivals in frame n by λ_n we write $\lambda_n = a\lambda_{n-1} + bw(n)$, where a and b are constants, $|a| < 1$, and w is a sequence of independent normally distributed random variables with mean η and variance σ^2, the latter is set to 1 for convenience.

The data available to us was not in terms of packets per frame but as successive interarrival times. We therefore defined a frame as the length of an average burst-silence cycle, [19, 20]. The parameters a, b and η of the model are matched to fit the mean, the variance and the first order correlation of the number of arrivals per frame.

2.3 The Switched Poisson Process

An SPP, switched Poisson process, is a Poisson process the rate of which is determined by the state of an underlying two state Markov chain. The transition rates of the Markov chain, denoted by γ (from 1 to 2) and ω (from 2 to 1), and the arrival rates associated with the two states, λ_1 and λ_2 respectively, are independent.

We have tried five different approaches to estimate the parameters of an SPP which are due to Meier-Hellstern [13, 14], Rossiter [17, 18], Heffes and Lucantoni [11], Gusella [10] and Okuda et al. [15] and in the sequel referred to as KMH, MR, HL, RG and OAS respectively.

The KMH approach is fairly complicated, but often shows the best agreement of all methods tested when applied to data generated by an SPP with known parameters. The basic idea is to find the parameters of the SPP that has the maximum likelihood of producing the observed sequence. This is done in an iterative way, although space does not allow us to go into detail.

The four others employ the index of dispersion $I(t)$ and the index of skewness $S(t)$ of the number of arrivals

$$I(t) = V\{N(t)\}/E\{N(t)\} \quad (2)$$
$$S(t) = T\{N(t)\}/E\{N(t)\} \quad (3)$$

where

$$V\{N(t)\} = E\{(N(t) - E\{N(t)\})^2\} \quad (4)$$
$$T\{N(t)\} = E\{(N(t) - E\{N(t)\})^3\} \quad (5)$$

for different values of t.

MR uses the mean m and the squared coefficient of variation C^2 of the interarrival times plus $I(t_1)$ and $I(t_2)$, where t_1 is of "medium length" and t_2 "substantially longer than t_1". In accordance with [17, 18], we have used $t_1 = 10m$ and $t_2 = 2.5t_1$.

HL use the mean m, the index of dispersion at $t = t_0, t_1$ and third moment of the number of arrivals, $T\{N(t_2)\}$. In accordance with [11] we have used $t_0 = t_2 = 10m$ and set t_1, which is "infinity", to $100m$.

RG uses four indexes of dispersion, at $t = t_0, t_1, t_2$ and the limit as $t \to \infty$. For t_0, which is to be of of "medium length", we have used $t_0 = 10m$. Also as suggested by [10], we have used $t_1 = t_0/2$ and $t_2 = 2t_0$. Finally we have assumed that the properties of infinity are essentially valid for $t = 100m$.

The last method, OAS, uses the mean arrival rate $\bar{r}$, $\lim_{t\to 0} \frac{d}{dt} I(t)$, $\lim_{t\to\infty} I(t)$ and $\lim_{t\to\infty} S(t)$. We have not used the formulae in [15] to express the four metrics in terms of the distribution of interarrival times since they rely on the traffic being renewal. Instead, we have assumed infinity after $100m$ and by estimating $I(t)$ at $t = 10^{-3}m$ and $t = m$, we take the slope as $\lim_{t\to 0} \frac{d}{dt} I(t)$.

2.4 The Switched Bernoulli Process

The switched Bernoulli process (SBP) is a discrete version of an SPP: To each of the two states in a discrete time Markov chain is associated a probability of a packet being generated at the end of a time slot. Transition probabilities are $1 - a$ from 1 to 2 and $1 - b$ from 2 to 1, while arrival probabilities are denoted by α and β for the two states respectively. It is convenient to associate arrivals with the state after a transition, i.e. the probability of an arrival during a transition from 1 to 1 is α, but β for a transition from 1 to 2, and so on. It is observed that the geometric model [9] is obtained as a special case of an SBP by setting $\alpha = 1$ and $\beta = 0$.

Due to the close relationship between SPPs and SBPs, fitting methods used for SPPs can be translated to SBPs too. However, due to the very small significance of discrete or continuous time scales [2, 3], it was assumed this was not likely to add much of interest to our investigation. Instead we used three of the four approaches developed by Solé et al. [19, 20] specifically for SBPs. Hence the model is denoted by SDG in what follows.

The first approach is to estimate the mean burst length $E\{L\}$, the mean silence length $E\{I\}$ and the arrival rates A_a and A_s of the two states respectively, which are then fitted to the model.

The second approach relies on parallels to pulse trains. Four parameters, viz. the cycle length $C = L + I$, the difference in arrival rates $\Delta A = A_a - A_s$, the relative length of a burst in a cycle B and the mean traffic intensity over a complete cycle R, are measured and fitted. This strategy has not been used since it tends to result in an incorrect mean arrival rate and hence makes comparisons with other models difficult.

The third approach is a modification of the second one. Having computed the parameters as in strategy 2, we set $A_s = 0$ and adjust the length of a stay in the silent state, I, so that the correct mean arrival rate is obtained.

Finally, in the fourth approach we match to B and the mean and the variance of the interarrival times.

2.5 The Markov-Hyperexponential Model

The Markov-hyperexponential model [8, 16], in the sequel abbreviated to MH2, suggests that bursts last for a negative exponentially distributed time the mean of which is $1/\mu$, while silence periods have a hyperexponential-2 distribution with parameters λ_1, λ_2 and α. The two stages of the hyperexponential distribution are assumed to represent two different types of silence, viz. pauses between talk spurts and pauses due to the other party of a conversation being active.

In the original proposal, the authors use empirical data due to [22]. The latter reports on the hardware of a specific speech detector and voice discriminator, the output of which is measured, in dBm, and classified as burst or silence accordingly. Since we cannot adopt such an approach here, we have used the burst/silence definition of [19, 20]. We have also assumed that arrivals occur according to a Poisson process at a rate of ρ while in the active state.

The model provides five parameters, but one is bounded by the constraint that a speaker on the average is active 50% of the time and is listening for the remaining 50%. This implies that the probability of finding the three state Markov chain in the listening state should equal the total probability of finding it in either the active state or the pause state. To solve for the four remaining parameters of the model, we use strategies 3 and 4 of [19, 20].

In strategy 3 we add the variance $V\{I\}$ of the silence lengths. When scaling the mean silence length, we also scale the variance so that the coefficient of variation C^2 remains constant and we adjust α to meet the speaking/listening constraint.

In strategy 4, the condition of fixed B gives μ. Next the mean and the variance of the interarrival times are used to find the arrival rate A_a and the mean of the hyperexponential silence distribution. (The variance of the latter is locked by the condition of constant C^2.) Again, α finally is used to match the requirement of 50% activity.

2.6 The Threshold Model

The threshold model [7], or TH for short, is a two state model with an active state and a silent, passive state. Following an arrival, the time to the next arrival is drawn from a distribution F_1. If, however, the value obtained is greater than a threshold T, the silent state is immediately entered for an independent time with distribution $F_2 \geq T$. F_1 and F_2 may in principle be chosen arbitrarily. In [7] are uniform, exponential, sine and combinations thereof considered, but we have chosen to limit ourselves to the case of both F_1 and F_2 being uniform.

Denoting the intervals of F_1 and F_2 by $(0, A_1)$ and (T, A_2) respectively, the three parameters of the model are A_1, A_2 and T. We determine these using strategies 3 and 4 of [19, 20], with a burst defined as a sequence of arrivals generated during one, uninterrupted stay in the arrival state.

3 Results

Tables 1 and 2 show, for a single source and multiple sources respectively, the observed behaviour in terms of interarrival times $\tilde{A}$, queue lengths at an arrival instant $\tilde{Q}$, time

Model	$\tilde{A}$	$\tilde{Q}$	$\tilde{T}$	$\tilde{D}$	$\tilde{B}$
	1.235(±0.001)	15.39(±0.040)	16.95(±0.032)	1.235(±0.001)	33.41(±0.113)
AMM	13.45(±0.022)	0.666(±0.017)	0.547(±0.017)	1.922(±0.009)	3.351(±0.085)
	3.993(±0.015)	1.577(±0.235)	1.582(±0.270)	10.44(±0.133)	5.660(±0.401)
	1.261(±0.000)	12.50(±0.050)	13.99(±0.047)	1.261(±0.000)	11.04(±0.079)
KMH	1.957(±0.006)	1.330(±0.036)	1.061(±0.031)	0.762(±0.005)	13.52(±0.560)
	3.258(±0.020)	2.046(±0.231)	2.047(±0.257)	6.248(±0.076)	10.23(±1.099)
	1.261(±0.001)	24.72(±0.120)	26.22(±0.113)	1.261(±0.001)	18.73(±0.129)
MR	4.061(±0.014)	1.131(±0.043)	1.005(±0.040)	1.441(±0.010)	14.71(±0.638)
	4.717(±0.031)	2.002(±0.318)	2.005(±0.332)	8.689(±0.138)	10.52(±1.226)
	1.261(±0.001)	37.67(±0.220)	39.17(±0.226)	1.261(±0.001)	17.45(±0.194)
OAS	3.361(±0.015)	1.173(±0.060)	1.085(±0.056)	1.328(±0.010)	26.71(±1.508)
	4.694(±0.044)	2.061(±0.435)	2.061(±0.448)	8.356(±0.174)	13.69(±1.962)
	1.260(±0.001)	36.85(±0.220)	38.35(±0.210)	1.260(±0.001)	26.65(±0.226)
RG	4.909(±0.024)	1.092(±0.059)	1.008(±0.055)	2.236(±0.019)	18.72(±0.808)
	6.831(±0.066)	2.043(±0.454)	2.045(±0.468)	10.99(±0.201)	10.47(±1.116)
	1.260(±0.001)	42.98(±0.310)	44.48(±0.307)	1.260(±0.001)	12.30(±0.159)
HL	2.222(±0.011)	1.338(±0.072)	1.249(±0.067)	0.855(±0.010)	43.59(±3.000)
	3.498(±0.038)	2.076(±0.435)	2.075(±0.445)	6.630(±0.166)	17.83(±2.883)
	1.287(±0.001)	13.77(±0.050)	15.27(±0.049)	1.287(±0.001)	11.96(±0.079)
SDG1	2.828(±0.007)	1.247(±0.036)	1.015(±0.029)	0.975(±0.007)	11.30(±0.446)
	3.360(±0.020)	2.040(±0.238)	2.038(±0.254)	6.557(±0.090)	9.666(±1.108)
	1.262(±0.001)	34.97(±0.180)	36.47(±0.178)	1.262(±0.001)	56.14(±0.275)
SDG3	16.23(±0.059)	1.030(±0.049)	0.946(±0.045)	4.723(±0.032)	5.790(±0.181)
	8.261(±0.061)	2.027(±0.400)	2.026(±0.410)	15.71(±0.259)	7.199(±0.639)
	1.262(±0.001)	24.02(±0.100)	25.52(±0.113)	1.262(±0.001)	43.59(±0.194)
SDG4	11.63(±0.038)	1.035(±0.039)	0.916(±0.035)	3.734(±0.022)	5.287(±0.158)
	7.685(±0.053)	2.014(±0.331)	2.018(±0.354)	14.03(±0.201)	6.779(±0.550)
	1.260(±0.001)	61.12(±0.410)	62.62(±0.421)	1.260(±0.001)	98.00(±0.501)
MH3	30.86(±0.164)	1.016(±0.063)	0.968(±0.060)	10.91(±0.105)	6.455(±0.202)
	14.48(±0.183)	2.005(±0.519)	2.004(±0.528)	25.51(±0.604)	7.264(±0.596)
	1.261(±0.001)	22.56(±0.090)	24.07(±0.097)	1.261(±0.001)	42.29(±0.194)
MH4	11.61(±0.041)	1.036(±0.041)	0.909(±0.035)	4.228(±0.026)	5.551(±0.163)
	8.907(±0.072)	1.977(±0.306)	1.985(±0.330)	15.51(±0.237)	6.804(±0.565)
	1.235(±0.001)	22.10(±0.090)	23.60(±0.081)	1.235(±0.001)	39.77(±0.178)
TH3	8.812(±0.019)	1.021(±0.038)	0.896(±0.035)	1.988(±0.010)	5.314(±0.161)
	4.719(±0.017)	1.961(±0.309)	1.961(±0.325)	8.661(±0.116)	7.253(±0.635)
	1.238(±0.001)	27.23(±0.120)	28.72(±0.113)	1.238(±0.001)	56.53(±0.226)
TH4	11.40(±0.032)	1.018(±0.040)	0.915(±0.039)	2.921(±0.017)	4.593(±0.131)
	6.120(±0.028)	1.982(±0.343)	1.979(±0.352)	10.39(±0.129)	6.641(±0.532)
	1.261(±0.006)	93.76(±6.640)	95.26(±6.647)	1.261(±0.006)	22.66(±4.496)
Dir.	11.63(±0.605)	1.612(±0.641)	1.561(±0.623)	8.027(±0.628)	100.4(±85.27)
	31.97(±5.850)	1.476(±1.681)	1.476(±1.702)	46.74(±11.57)	34.15(±32.28)

Table 1: *Results for a single source.*

spent in system $\tilde{T}$, interdeparture times $\tilde{D}$ and server busy periods $\tilde{B}$ with the mean service time taken as the unit of time. The three rows show the mean, the coefficient of variation and the coefficient of skewness respectively. Denoting the rth central moment by μ_r, the two latter are defined as $\mu_2(\tilde{X})/\mu_1(\tilde{X})^2$ and $\mu_3(\tilde{X}^3)/\mu_2(\tilde{X})^{\frac{3}{2}}$ respectively. For

Model	$\tilde{A}$	$\tilde{Q}$	$\tilde{T}$	$\tilde{D}$	$\tilde{B}$
	1.236(±0.001)	26.40(±0.050)	27.89(±0.049)	1.236(±0.001)	53.42(±0.162)
AMM	20.61(±0.017)	0.634(±0.013)	0.568(±0.012)	3.162(±0.013)	2.721(±0.051)
	5.613(±0.059)	1.241(±0.150)	1.252(±0.180)	13.09(±0.947)	3.925(±0.221)
	1.260(±0.000)	2.613(±0.016)	4.108(±0.016)	1.260(±0.000)	7.081(±0.061)
KMH	1.022(±0.005)	2.417(±0.129)	0.976(±0.054)	0.416(±0.004)	6.225(±0.444)
	2.064(±0.029)	4.763(±0.940)	4.776(±1.080)	4.463(±0.105)	16.50(±3.566)
	1.262(±0.002)	4.166(±0.050)	5.662(±0.051)	1.262(±0.002)	7.200(±0.092)
MR	1.043(±0.005)	4.360(±0.368)	2.359(±0.193)	0.437(±0.005)	12.53(±1.270)
	2.137(±0.048)	6.050(±1.383)	6.050(±1.467)	4.668(±0.196)	25.79(±6.506)
	1.261(±0.002)	3.628(±0.071)	5.124(±0.071)	1.261(±0.002)	7.295(±0.103)
OAS	1.029(±0.007)	5.636(±0.977)	2.824(±0.476)	0.424(±0.006)	13.82(±3.065)
	2.093(±0.058)	9.298(±4.489)	9.306(±4.657)	4.570(±0.241)	58.89(±52.79)
	1.259(±0.001)	3.177(±0.054)	4.672(±0.053)	1.259(±0.001)	7.221(±0.125)
RG	1.027(±0.009)	4.613(±0.682)	2.131(±0.310)	0.420(±0.008)	10.93(±1.836)
	2.076(±0.059)	8.969(±3.587)	8.983(±3.783)	4.509(±0.231)	40.45(±17.81)
	1.260(±0.001)	3.341(±0.073)	4.836(±0.073)	1.260(±0.001)	7.150(±0.099)
HL	1.026(±0.009)	6.135(±1.392)	2.926(±0.650)	0.420(±0.007)	12.00(±2.150)
	2.073(±0.054)	13.10(±8.250)	13.12(±8.463)	4.498(±0.220)	53.36(±27.53)
	1.287(±0.000)	3.611(±0.026)	5.105(±0.026)	1.287(±0.000)	6.795(±0.052)
SDG1	1.059(±0.005)	3.343(±0.162)	1.672(±0.082)	0.476(±0.004)	9.576(±0.597)
	2.184(±0.026)	4.648(±0.653)	4.649(±0.728)	4.553(±0.094)	17.10(±3.064)
	1.262(±0.001)	8.970(±0.122)	10.46(±0.121)	1.262(±0.001)	7.745(±0.094)
SDG3	1.104(±0.006)	4.558(±0.349)	3.350(±0.251)	0.490(±0.006)	27.03(±2.322)
	2.362(±0.050)	4.582(±0.860)	4.581(±0.895)	5.166(±0.180)	25.70(±5.174)
	1.262(±0.001)	5.607(±0.062)	7.103(±0.063)	1.262(±0.001)	7.495(±0.079)
SDG4	1.070(±0.006)	4.169(±0.295)	2.599(±0.179)	0.460(±0.005)	17.99(±1.535)
	2.235(±0.042)	4.911(±0.950)	4.908(±1.001)	4.891(±0.166)	24.95(±5.571)
	1.260(±0.002)	10.88(±0.220)	12.37(±0.218)	1.260(±0.002)	7.772(±0.129)
MH3	1.108(±0.008)	5.490(±0.622)	4.246(±0.469)	0.489(±0.007)	36.74(±4.682)
	2.368(±0.069)	5.156(±1.383)	5.157(±1.421)	5.208(±0.266)	37.49(±12.25)
	1.261(±0.001)	4.948(±0.053)	6.444(±0.053)	1.261(±0.001)	7.496(±0.080)
MH4	1.072(±0.006)	3.836(±0.278)	2.262(±0.160)	0.458(±0.005)	14.95(±1.369)
	2.234(±0.042)	5.066(±1.046)	5.068(±1.113)	4.879(±0.156)	25.00(±6.981)
	1.235(±0.001)	6.451(±0.071)	7.947(±0.071)	1.235(±0.001)	7.872(±0.078)
TH3	1.021(±0.005)	4.448(±0.275)	2.930(±0.175)	0.398(±0.004)	20.12(±1.429)
	2.071(±0.038)	4.436(±0.641)	4.440(±0.685)	4.749(±0.169)	21.90(±3.702)
	1.238(±0.001)	5.514(±0.081)	7.010(±0.081)	1.238(±0.001)	7.631(±0.087)
TH4	1.010(±0.005)	5.680(±0.457)	3.516(±0.274)	0.390(±0.005)	20.13(±1.920)
	2.035(±0.043)	5.537(±0.991)	5.534(±1.043)	4.627(±0.182)	29.95(±8.352)
	1.192(±0.013)	8.813(±1.910)	10.31(±1.908)	1.192(±0.013)	9.583(±1.375)
Dir.	1.026(±0.088)	6.634(±4.673)	4.846(±3.414)	0.335(±0.073)	28.42(±27.57)
	2.066(±0.640)	4.634(±4.318)	4.636(±4.455)	5.088(±2.992)	47.39(±37.16)

Table 2: *Results for multiple sources.*

each moment, we display the 95% confidence intervals.

In Table 1 the results for the single source case show that the mean interarrival and interdeparture times match exactly as we would have expected because the system is conserving packet flows and all models were fitted to yield the same average load. However, the various models all exhibit different higher moments in their interarrival distributions and we are able to see the impact which they make upon the server busy periods, time spent in the system and queue lengths. It is also worth observing that, in each model, the coefficient of variation has *decreased* significantly on the output (departure process) as compared to the input (arrival process) but, at the same time, the corresponding skewness coefficients have shown an *increase*.

A study of the second moments for the interarrival times shows that the MH2 , SDG and AMM models (in that order) have the greatest degree of "burstiness". The pattern of server busy periods matches precisely the relativities in the variance peaks exhibited by the interarrival process. It is also approximately true that the larger the coefficient of variance in the interarrival time, the longer the queue length and time spent in the system. Exceptions in this case are the MR, OAS and RG models, all based upon the Switched Poisson Process, which give queue lengths and times in the system that are disproportionately higher than their interarrival coefficients of variance would indicate when compared to the other models. In carrying out our studies we were amazed by the differences in performance from a given model which arose simply through changing the fitting method! These differences have previously been observed [19, 20] with respect to the SDG model and we have confirmed their ordering of performance. This is clearly shown by the results in the table for each of the SPP, SDG and MH2 models. Finally, we note that for the server busy time metric, the mean value is substantially greater than the coefficient of variance in all cases except the KMH and OAS models where the position has been reversed.

Turning our attention to Table 2, we note smoother arrival processes (the smoothness is, in fact, preserved in the departure process) and that many of our observations for the single source case can also be applied to the multiple source cases. Note however, that the multiple source cases generally have shorter queue lengths, less time spent in the system and shorter busy periods when compared with the single source models but that the variation and skewness are actually *increased* for all metrics. An exception to this rule is the performance of the AMM which actually gives substantially longer busy periods, queue lengths and times spent in the system. The interarrival and interdeparture times for the two sets of results are comparable between the single and multiple source cases so this cannot have contributed to this difference. On the other hand, the AMM model is built around the concept of frames with batch arrival of the packets (we assume that all packets are placed at the head of the frame) and this is quite a different approach from the other models. We believe that this has contributed to the unusual behaviour of the AMM model in this case.

In order to ascertain which, if any, of the models tested in our study gives a good match to the performance of the "real" traffic which we used to determine the parameters of the models, we conducted an experiment in which this data was passed through the deterministic server and the performance results recorded. The output from this experiment is recorded in the column headed Dir. It will be seen that for the single source case, the variance is comparable with many of the other models, but the skewness is considerably greater than the values from the other models. This seems to produce long queue lengths, long busy server periods and times in the system for this data.

4 Conclusions

In this paper we have considered a number of bursty traffic models and tested their performance as they have passed through a deterministic server. This performance has been compared both with the real data from which the model parameters were fitted and also between the various types of models. The aim of the study was to establish whether any of these models could accurately track the observed "real performance". This procedure seems simple and obvious enough — except that our real data stream sequence was considerably shorter than the simulation run data sequences and this makes accurate conclusions difficult. In addition, it is not clear whether the "real" data stream which we have used can be wholly relied upon to represent a *typical* traffic stream entering an ATM network. For example, it is possible to use voice, data or video traffics and to obtain good fits to one or other of the models which we have considered. The difficulty seems to be that it is very hard to find a model which is universally acceptable and adaptable to the multiplicity of different traffic types expected to be present in future ATM or multiservice networks. In earlier studies we considered single source situations which could be expected to occur at the entrance to a network, the present paper has extended this work and we have also reported studies of multiple source cases which would be typical of the behaviour of traffic streams moving inside of the network. We have shown that each of the various models which have been published and investigated using our techniques has quite different performance characteristics both in single and multiple source contexts and that it is difficult to decide whether any particular model can be used to predict the performance of multiservice traffic streams in a future network.

Acknowledgement

This research was carried out under contract no. 7090 to Telecom Australia. The permission of the Executive General Manager Research to publish this paper is gratefully acknowledged.

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