Fitting Algorithms for MMPP ATM Traffic Models

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ABSTRACT

In this paper, we propose and study fitting algorithms for MMPP(2) and CMPP ATM traffic models, which are special cases of Markov Modulated Poisson Processes (MMPP). Two fitting algorithms, both based on the cell interarrival times, are considered for the MMPP(2) model: one fits the cumulative distribution and auto-covariance functions and other fits the first three moments and auto-covariance function. The fitting algorithm for the CMPP model is based on the cumulative distribution and auto-covariance functions of the arrival rate. The MMPP(2) is evaluated as a model for the superposition of IPP sources; the CMPP is evaluated as a model for MMPP(2), MMPP(3), MMPP(5), IPP, IDP, Pareto and Self-Similar traffic. The proposed algorithms can be used in the characterisation of ATM traffic streams and in connection admission control procedures.

KEYWORDS

MMPP, CMPP, cumulative distribution function, auto-correlation, auto-covariance, Cell Loss Ratio, Average Waiting Time.

1. INTRODUCTION

Broadband networks based on ATM technology are expected to carry a variety of traffic types, with multiple characteristics and requirements, in an integrated fashion. The design and control of these networks is carried out using a set of parameters that describe the main traffic characteristics (e.g. the peak cell rate, the maximum burst size, etc.). Therefore it is important to capture cell arrival flows and describe them through suitable stochastic models. An appropriate traffic model allows a better resource utilisation without performance losses. A traffic model is a mathematical description of a specific traffic type. In order to build a mathematical model from a measured cell arrival flow, some of its statistics must be known. For example, the mean, variance and auto-correlation function of the cell interarrival time process or the mean, variance and peakedness of the cell counting process. These statistics are measured or calculated from observed traffic data. The actual set of statistics used in the inference process depends on the impact that those statistics may have in the main performance measures.

An effective traffic model has to reproduce the first and second order statistics of the original traffic sample. The distribution function defines the first order statistics whereas the second order statistics can be accounted for by the auto-correlation function. The second order statistics play an important role in traffic modelling, because traffic auto-correlation is an important factor in ATM cell losses due to buffer and bandwidth limitations.

The Markov Modulated Poisson Process with two states, MMPP(2), is a non-renewal model that has been widely used for modelling ATM traffic. In this paper, we present and compare two fitting algorithms for the MMPP(2) model, based on the characterisation of the cell interarrival time process: one approach fits the complementary cumulative distribution function (CDF) and the auto-covariance function (and is adapted from the study reported in [1]); the other approach fits the first three moments and the auto-covariance function.

The Circulant-Modulated Poisson Process (CMPP) is a particular case of the MMPP process, where restrictions in the transition rate matrix assure that the N states of the MMPP process are equiprobable. In this paper, we present a modelling methodology for the CMPP process based on the characterisation of the arrival rate CDF and auto-covariance functions (adapted from the study reported in [3] and [4]).

This paper is organised as follows. In sections 2 and 3 we present and study the fitting algorithms for the MMPP(2) and CMPP models, respectively. Finally, in section 4, some conclusions are drawn.

2. FITTING ALGORITHMS FOR THE MMPP(2) MODEL

The defining parameters of the MMPP(2) model are ([2]):

$$Q = \begin{bmatrix} -r_1 & r_1 \\ r_2 & -r_2 \end{bmatrix};\ \Lambda = \begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix};$$

$$p = \frac{1}{\lambda_1 r_2 + \lambda_2 r_1}\begin{bmatrix} \lambda_1 r_2 & \lambda_2 r_1 \end{bmatrix} \qquad (1)$$

where Q represents the infinitesimal generator, Λ is the matrix of the Poisson arrival rates and p is the initial probability vector of the underlying Markov process.

Assume interval-stationary MMPP(2) processes where X_i represents the interarrival time between the i^{th} and $(i+1)^{th}$ cells. In this case, the distribution of the interarrival time X_i is a second order *hyperexponential distribution* (H_2) [2], with complementary CDF:

$$\begin{aligned} F_c(x) &= pe^{(Q-\Lambda)x}(\Lambda - Q)^{-1}\Lambda e \\ &= qe^{-u_1 x} + (1-q)e^{-u_2 x},\ 0 < q < 1 \end{aligned} \qquad (2)$$

and density function:

$$f(x) = qu_1 e^{-u_1 x} + (1-q)u_2 e^{-u_2 x},\ 0 < q < 1 \qquad (3)$$

The three parameters of the hyperexponential distribution, u_1, u_2 and q, can be related with the MMPP(2) parameters by:

$$u_1 = \frac{\lambda_1 + \lambda_2 + r_1 + r_2 - \delta}{2}\ ;\ u_2 = \frac{\lambda_1 + \lambda_2 + r_1 + r_2 + \delta}{2}\ ;$$

$$q = \frac{\lambda_2 r_1^2 + \lambda_1^2 r_2}{(\lambda_2 r_1 + \lambda_1 r_2)(u_1 - u_2)} - \frac{u_2}{u_1 - u_2} \qquad (4)$$

where $\delta = \sqrt{(\lambda_1 - \lambda_2 + r_1 - r_2)^2 + 4r_1 r_2}$.

The auto-covariance function, C[k], $k \geq 1$, is given by ([1]):

$$\begin{aligned} C[k] &= E[(X_1 - E\{X_1\})(X_{k+1} - E\{X_{k+1}\})] \\ &= p(\Lambda - Q)^{-2}\Lambda\left\{\left((\Lambda - Q)^{-1}\Lambda\right)^{k+1} - ep\right\}(\Lambda - Q)^{-2}\Lambda e \\ &= A\sigma^k \end{aligned} \qquad (5)$$

where

$$A = \frac{(\lambda_1 - \lambda_2)^2 r_1 r_2}{(\lambda_2 r_1 + \lambda_1 r_2)^2(\lambda_1\lambda_2 + \lambda_2 r_1 + \lambda_1 r_2)}$$

$$\sigma = \frac{\lambda_1\lambda_2}{(\lambda_1\lambda_2 + \lambda_2 r_1 + \lambda_1 r_2)} \qquad (6)$$

In the following section we present two fitting algorithms for the MMPP(2) model. Both procedures estimate the parameters u_1, u_2, q and σ.

2.1 The interarrival time distribution inference procedure

In this approach, u_1, u_2, q are estimated by fitting the empirical and theoretical complementary CDFs and σ is estimated by fitting the empirical and theoretical auto-covariance functions. We have used non-linear fitting techniques (the *NonlinearFit* function of MATHEMATICA). This approach is different from the one adopted in [1]. Figure 1 illustrates the application of this procedure to one of the scenarios under consideration (to be described in section 2.3).

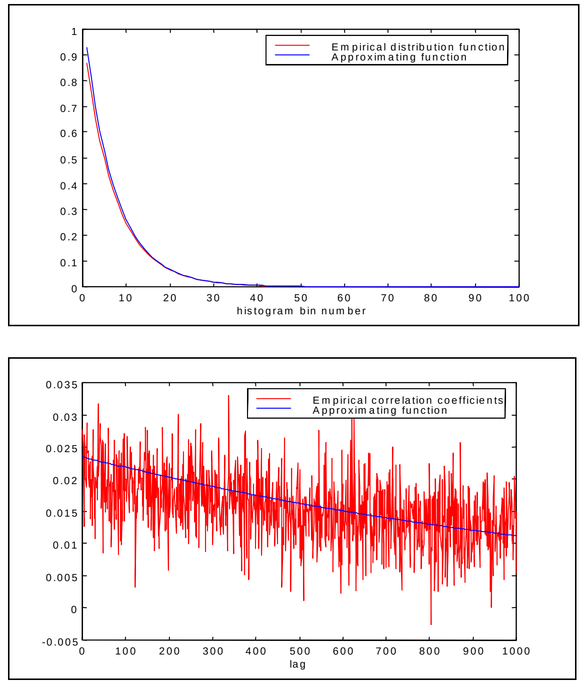


Figure 1: (Up) Fitting the interarrival time complementary distribution to an hyper-exponential function; (Down) Fitting the auto-correlation to an exponential function

The upper part of Figure 1 represents the fitting of the complementary CDFs. As can be seen, both curves are very close to each other. The lower part of Figure 1 represents the fitting of the auto-correlation functions. In this case, the approximation is not so good and the exponential function can only capture the mean behaviour of the empirical auto-correlation.

The parameters of the MMPP(2), λ_1, λ_2, r_1 and r_2, can be calculated from the estimated parameters u_1, u_2, q and σ, through:

$$\lambda_1 = \frac{1}{2}\left[q(1-\sigma)(u_1 - u_2) + \sigma u_1 + u_2 + \sqrt{\xi}\right] \qquad (7a)$$

$$\lambda_2 = \frac{u_1 u_2\{\lambda_1 - q(u_1 - u_2) - u_2\}}{\lambda_1 u_1 - \lambda_1 q(u_1 - u_2) - u_1 u_2} \qquad (7b)$$

$$r_1 = \frac{(u_1 - \lambda_1)(u_2 - \lambda_1)}{\lambda_2 - \lambda_1} \qquad (7c)$$

$$r_2 = \frac{(\lambda_2 - u_1)(\lambda_1 + r_1 - u_1)}{u_1 - \lambda_1} \qquad (7d)$$

where $\xi = [q(1-\sigma)(u_1 - u_2) + \sigma u_1 + u_2]^2 - 4\sigma u_1 u_2$.

2.2 The interarrival time moments inference procedure

In this approach, u_1, u_2, q are estimated by fitting the empirical and theoretical first three moments of the interarrival time and σ is estimated as in previous section.

From equation (3), we obtain the Laplace transform of $f(x)$:

$$f(s)=\frac{qu_1}{s+u_1}+\frac{(1-q)u_2}{s+u_2} \qquad (8)$$

The first three moments are given by the derivatives of (8) calculated at $s=0$:

$$m_1=\frac{q}{u_1}+\frac{1-q}{u_2}=q\gamma_1+(1-q)\gamma_2 \qquad (9a)$$

$$m_2=\frac{2q}{u_1^{\,2}}+\frac{2(1-q)}{u_2^{\,2}}=2q\gamma_1^{\,2}+2(1-q)\gamma_2^{\,2} \qquad (9b)$$

$$m_3=\frac{6q}{u_1^{\,3}}+\frac{6(1-q)}{u_2^{\,3}}=6q\gamma_1^{\,3}+6(1-q)\gamma_2^{\,3} \qquad (9c)$$

considering that $\gamma_i=1/u_i$. Introducing the relative second moment $r=m_2/2m_1^{\,2}$ and the relative third moment $k=m_3/6m_1^{\,3}$, the H_2 parameters are given by:

$$\gamma_1=\frac{m_1\left(k-r+\sqrt{k^2+k(4-6r)+r^2(-3+4r)}\right)}{2(-1+r)} \qquad (10a)$$

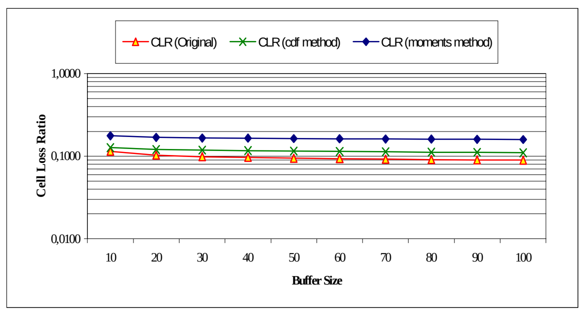
$$\gamma_2=-\frac{m_1\left(-k+r+\sqrt{k^2+k(4-6r)+r^2(-3+4r)}\right)}{2(-1+r)} \qquad (10b)$$

$$\begin{aligned}q=\frac{m_1-\gamma_2}{\gamma_2-\gamma_2}&=(k^2-3r^2+4r^3-\\&-2\sqrt{k^2+k(4-6r)+r^2(-3+4r)}+\\&+3r\sqrt{k^2+k(4-6r)+r^2(-3+4r)}-\\&-k\left(-4+6r+\sqrt{k^2+k(4-6r)+r^2(-3+4r)}\right))/\\&/(2(k^2+k(4-6r)+r^2(-3+4r)))\end{aligned} \qquad (10c)$$

2.3 Results and discussion

The evaluation of the inference procedures resorts to a superposition of traffic sources. We compare the cell loss ratio (CLR) and the average waiting time (AWT) obtained when feeding a buffer with constant service rate and finite capacity (i) directly with a set of individual traffic sources and (ii) with MMPP(2) traffic, where the MMPP(2) parameters where inferred from the traffic generated by the set of traffic sources of step (i), using the inference procedures described above. Each individual source is modelled by an Interrupted Poisson Process (IPP), and two types of such sources are considered: type 1, with mean ON and OFF durations of 350 ms and 650 ms, respectively, and with a mean interarrival time in the ON state of 12ms; and type 2, where the mean ON and OFF durations are 350 ms and 5800 ms, respectively, and in the ON state the mean interarrival time is 1.2 ms. The output link capacity is assumed as 1.5 Mb/s. Two sets of traffic sources were considered in this study: the first one consists of the superposition of 120 type 1 sources (homogeneous case) and the second one of the superposition of 80 type 1 and 10 type 2 sources (heterogeneous case). These scenarios where also considered in [1].

The results obtained for each scenario are represented in Figure 2 and Figure 3. We will refer to the results obtained when driving directly the buffer with the set of traffic sources as the original case.



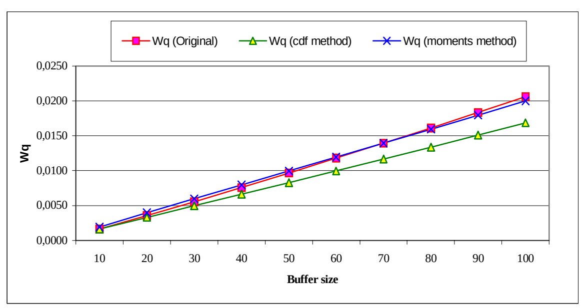
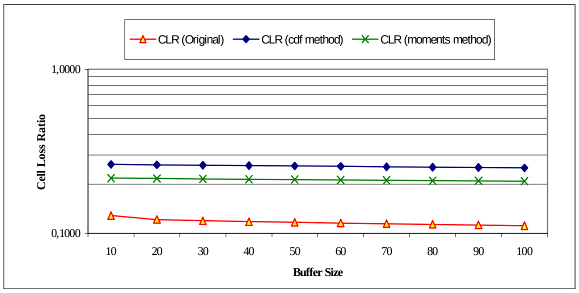


Figure 2: Results for scenario 1 (homogeneous case): (Up) comparison of the CLR values; (Down) comparison of the average waiting time values



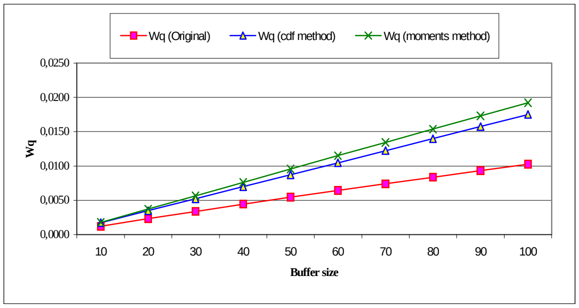


Figure 3: Results for scenario 2 (heterogeneous case): (Up) comparison of the CLR values; (Down) comparison of the average waiting time values

From Figure 2, we can see that for the homogeneous scenario both inference procedures provide good results. Concerning the CLR, the CDF method gives results that are almost coincident with the original case. The moments method gives slightly worse results. Both curves corresponding to the inference procedures have nearly the same slope of the curve obtained with the original traffic. We note also that, in this case, the CLR values obtained with both inference procedures are greater than the CLR corresponding to the original traffic yielding upper estimates of the CLR.

Regarding the AWT, the results obtained using the inference procedures are also close to the original ones. The moments method, for example, matches almost perfectly the original curve. The CDF method, on the other hand, underestimates the AWT, especially for larger buffer sizes, but this underestimation never exceeds 20% of the corresponding original value.

Observing Figure 3, we see that for the heterogeneous case the modeling based on the inference procedures always yield greater CLR and AWT values. The results obtained are globally worse than the ones corresponding to the homogeneous case. This behavior is partly due to a more accurate fitting of the auto-correlation function in the homogeneous case, because this function has less variability.

3. FITTING ALGORITHM FOR THE CMPP MODEL

The CMPP is a special case of a Markov Modulated Poisson Process. Like the MMPP a Markov chain modulates the CMPP, but in the CMPP the transition rate matrix has to obey the following form:

$$Q = \begin{bmatrix} a_0 & a_1 & a_2 & \dots & a_{N-1} \\ a_{N-1} & a_0 & a_1 & \dots & a_{N-2} \\ \dots & a_{N-1} & a_0 & \dots & a_{N-3} \\ \dots & \dots & \dots & \dots & \dots \\ a_1 & a_2 & a_3 & \dots & a_0 \end{bmatrix} = circ(\vec{a}) \qquad (11)$$

where $\vec{a} = [a_0 a_1 \dots a_{N-1}]$. In summary, if $a_{i,j}$ is the transition rate between state *i* and state *j*, then

$$\begin{cases} a_{i,j} = a_{i+1,j+1} & i < N, j < N \\ a_{N,j} = a_{1,j+1} \\ a_{i,N} = a_{i+1,1} \end{cases} \qquad (12)$$

Like the MMPP, the CMPP has an associated vector describing the Poisson arrival rate in each state $\vec{\gamma} = [\gamma_0 \quad \gamma_1 \quad \dots \quad \gamma_{N-1}]$. The main advantages of the CMPP, over the MMPP, is the possibility of constructing $(Q, \vec{\gamma})$ from measured data without the necessity of solving an inverse eigenvalue problem which has no general solution and the fact that CMPP states are equiprobable.

3.1 CMPP inference procedure

In this paper, the CMPP model construction methodology, first described in [3] and [4], was adapted and tested with different kinds of traffic streams. The entire methodology is based on the characterisation of a arrival rate. The following steps are required to construct a CMPP model from the measured data: (i) fitting the empirical auto-correlation function with a weighted sum of exponential functions; (ii) determine the circulant vector $\vec{a}$ from the time constants of the exponential functions, (iii) determine the rate vector $\vec{\gamma}$ from the empirical distribution and auto-correlation functions.

At the first step, the empirical auto-correlation $R(\tau)$ is fitted to the weighted sum of exponential functions

$$R_p(\tau) = \sum_{l=o}^{M-1} \Psi_l \cdot e^{\lambda_l |\tau|} \qquad (13)$$

with Ψ_l real non-negative. The calculation of the Ψ_l and λ_l coefficients is based on the Prony algorithm. We have restricted $R_p(\tau)$ to be a sum of two exponential functions, to improve speed and because most traffic types have auto-correlation with exponential or hyper-exponential behaviour. However, if required, more exponential functions can be used in the fitting process. The Prony method does not assure non-negative Ψ_l values. In this case, the following procedure is used: (i) an expansion of the λ_l set is made, i.e., some new values are added using linear interpolation; (ii) a non-negative least squares algorithm, matching $R(\tau)$, is used to calculate new Ψ_l values, (iii) only positive Ψ_l and its associated λ_l values are used (we denote the number of positive Ψ_l values by *L*).

The second order statistics of a CMPP are represented by

$$\vec{\lambda} = \sqrt{N}\vec{a}F^{*} \tag{14}$$

and

$$\vec{\beta} = \frac{1}{\sqrt{N}}\vec{\gamma}F^{*} \tag{15}$$

where F^* represents the conjugate transpose Fourier matrix. Vector $\vec{\beta}$ can be decomposed in a power vector

$$\vec{\Psi} = \left|\vec{\beta}\right|^2 = \frac{1}{N}\left|\vec{\gamma}F^{*}\right|^2 \tag{16}$$

and a phase vector

$$\vec{\theta} = \arg\{\vec{\beta}\} = \arg\{\vec{\gamma}F^{*}\} \tag{17}$$

In the second step, equation (14) is used to calculate vector $\vec{a}$. The number of states *N* is pre-defined; generally 100 states are sufficient. Vector $\vec{\lambda}$ is a vector with *N* elements, where $L < N$ are the λ_l calculated in previous step and the remaining $N - L$ have zero values. At this point, both the position of the λ_l elements in the $\vec{\lambda}$ vector and vector $\vec{a}$ are unknowns. The solution of equation (14) is found by combining an index search algorithm (that changes the positions of the λ_l elements) and a phase I simplex algorithm. The positions of the Ψ_l elements in the $\vec{\Psi}$ vector are the same as the positions of the λ_l elements in the $\vec{\lambda}$ vector.

To construct the vector $\vec{\gamma}$ (third step) we need to determine an empirical vector for the rates associated with each state. This vector will be denoted by $\vec{\gamma}_e$. The empirical rates are found by inverting the empirical distribution function, under the condition that all states are equiprobable, i.e., $\gamma_{en} = F^{-1}\left(\frac{n}{N}\right)$, $n = 0, 1, ..., N-1$.

To obtain $\vec{\gamma}$, the function

$$\sum_{n=0}^{N-1}\left|\gamma_{en} - \gamma_n\right| \tag{18}$$

has to be minimised. The γ_n elements can be obtained by inverting equation (15):

$$\gamma_n = \bar{\gamma} + \sum_{l=1}^{N-1}\sqrt{\Psi_l}\cos(2\pi nl / N - \theta_l)\,. \tag{19}$$

Note that the Ψ_l values and positions have already been calculated in previous steps.

3.2 Results and discussion

The inference procedure of the CMPP parameters described in previous section was tested by comparing the CLR obtained when driving a buffer with finite capacity and constant service rate with (i) data generated (through simulation) by the original CMPP model and (ii) data generated by the a CMPP model which was inferred (using the procedure of previous section) from data generated in step (i). We also compared some statistics of the original and modelled data: mean, standard deviation, maximum, minimum, Hurst parameter and peakedness.

We tested the CMPP model (and its inference procedure) as an approximation to different types of traffic. We considered MMPP(2), MMPP(3), MMPP(5), IPP, IDP, Pareto and Self-similar traffic models. The comparison was made using the above procedure. The Hurst parameter (H. P.) and peakedness (Peaked.) were considered in order to assess the self-similar behaviour of the generated traffic streams. These two parameters were measured using the methods described in [5].

The first step in this test was to apply the inference procedure to traffic streams of 500000 cells generated according to the several models referred above: CMPP with 100 states, MMPP(2), MMPP(3), MMPP(5), IPP, IDP, Pareto, and Self-similar traffic with H=0.8 and H=0.6. Self-similar traffic was generated through the methods described in [6].

The second step is the generation of the CMPP traffic using the results of the inference procedure. Here 10 replicas of 200000 cells each are generated. The comparison of the statistics of original and modelled traffic is made in Table 1. The table shows the mean and 95% confidence intervals corresponding to the 10 replicas.

		Mean	Max	Min	Std	H. P.	Peaked.
CMPP	O	2275.3	3470	0	615.61	0.7287	0.1297
	M	2135.9 ±37.03	3262 ±39.6	0 ±0	524.77 ±35.47	0.7803 ±0.021	0.1171 ±0.008
MMPP(2)	O	1341.2	5900	100	976.21	0.9101	0.3032
	M	1324.6 ±34.04	6030 ±185.4	0 ±0	857.0 ±23.73	0.9135 ±0.006	0.2704 ±0.002
MMPP(3)	O	1056.3	6200	0	1147	0.8557	0.4614
	M	972.68 ±45.33	6240 ±82.8	0 ±0	1023 ±23.3	0.8687 ±0.003	0.4469 ±0.018
MMPP(5)	O	2303.5	3530	0	779	0.7315	0.1532
	M	2263.9 ±54.2	3479 ±37.7	0 ±0	665 ±48.4	0.7820 ±0.019	0.1382 ±0.011
IPP	O	865.11	4440	0	1503	0.7272	0.7323
	M	743.40 ±42.3	4480 ±82.6	0 ±0	1310 ±40.3	0.8230 ±0.008	0.7400 ±0.02
IDP	O	645.6	4010	0	1276.7	0.6272	0.8611
	M	612.3 ±31.8	4455 ±52.2	0 ±0	1235.2 ±43.9	0.7300 ±0.025	0.8636 ±0.02
Pareto	O	3999.8	4940	3200	299	0.5537	0.0371
	M	3949.1 ±47.2	4848 ±64.2	3131 ±65.9	310 ±11.3	0.7403 ±0.02	0.039 ±0.002
S-S H=0.6	O	2065.6	2250	1890	66.3	0.8093	0.0182
	M	2059.5 ±9.98	2498 ±22.6	1619 ±25.1	146.6 ±3.51	0.6609 ±0.044	0.0338 ±0.0009
S.SH=0.8	O	1841.7	1890	1790	16.2	0.5995	0.0060
	M	1821.9 ±16.5	2261 ±25.4	1425 ±26.8	134.9 ±3.00	0.4849 ±0.04	0.0405 ±0.002

Table 1: Statistics of original (O) and modelled (M) traffic streams.

The third step was to drive a buffer with finite capacity and constant service rate with the original and modelled traffic streams, and estimate the CLR through simulation. The results are presented in Table 2.

		Buffer Len.	Trans. Rate	CLR
CMPP	O	500 cells	1 Mbps	2.63E-2
	M			5.20E-3 ± 1.8E-3
MMPP(2)	O	500 cells	1 Mbps	1.01E-2
	M			1.44E-02 ± 3.9E-3
MMPP(3)	O	500 cells	1 Mbps	1.04E-3
	M			4.30E-03 ± 1.6E-3
MMPP(5)	O	1000 cells	1 Mbps	3.8E-2
	M			2.36E-02 ± 7.3E-3
IPP	O	1000 cells	1 Mbps	3.23E-2
	M			5.73E-2 ± 9.2E-3
IDP	O	500 cells	1 Mbps	6.06E-2
	M			5.81E-2 ± 2.77E-2
Pareto	O	100 cells	1.7 Mbps	6.58E-3
	M			1.45E-2 ± 4.5E-3
S-S H=0.6	O	100 cells	800 Kbps	8.61E-2
	M			8.32E-2 ± 4.6E-3
S-S H=0.8	O	100 cells	780 Kbps	8.55E-4
	M			3.2E-3 ± 2.3E-3

Table 2: CLR for the original (O) and modelled (M) traffic streams.

The application of the inference procedure to CMPP traffic, shows that the procedure can capture all major statistics of the original traffic. The statistics of the original traffic are close to the confidence intervals of the modelled traffic. This is also true for the CLR. In Figure 4 and Figure 5, we show the CDF and the auto-correlation function of the original and modelled traffic.

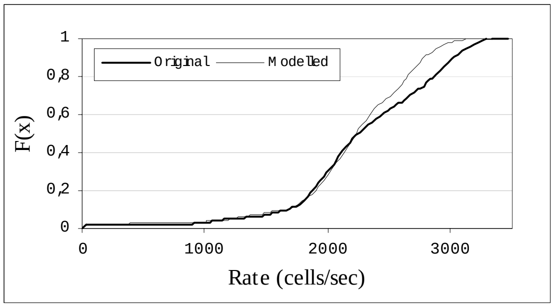


Figure 4: CDF for the CMPP original traffic rate (darker) and modelled traffic rate.

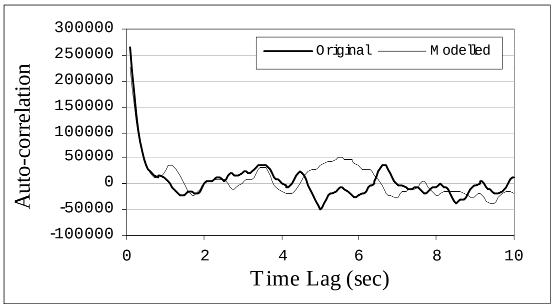


Figure 5: Auto-correlation function for the CMPP original traffic (darker) and modelled traffic.

In Figure 6 it can be seen that the CDF of the modelled traffic has softer transitions than the CDF of the original MMPP(3) traffic, reflecting the existence of only three states in the Markov chain. However the overall behaviour of the two CDFs is similar. The same is true for the auto-correlation function as represented in Figure 7.

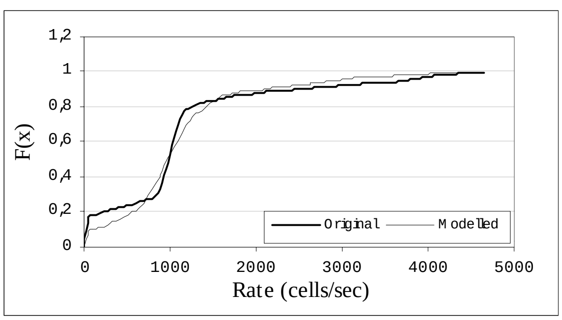


Figure 6: CDF for the original MMPP(3) traffic (darker) and modelled traffic rate.

It can be concluded that, under the conditions assumed in this study, MMPP(2), MMPP(3), MMPP(5) and IPP traffic are well approximated by the CMPP model. Some differences observed in the CLR we believe can be attributed to the number of generated cells not being sufficiently large.

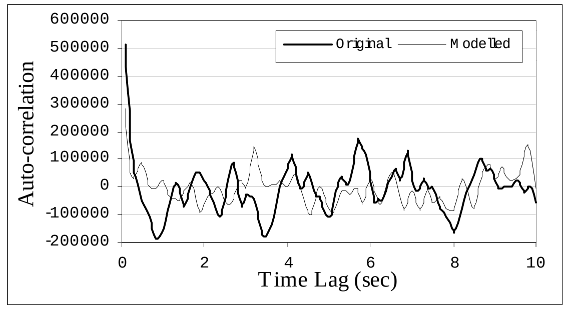


Figure 7: Auto-correlation function for the original MMPP(3) traffic (darker) and modelled traffic.

The above conclusions also apply to IDP traffic. The CDF curves, Figure 8, shows that the ON state of the original IDP traffic (with a rate of 4000 cells/s) is not matched perfectly since the CDF of the modelled traffic is not able to follow the sharp transition around 4000 cells/s of the original CDF. However, this mismatch around the peak rate does not seem to have a great influence in the main traffic characteristics.

Pareto traffic is not well modelled by the CMPP. Pareto traffic has an auto-correlation that is theoretically zero but the CMPP inference procedure can not reflect this behaviour. The modelled traffic has higher auto-correlation (Figure 9) as well higher Hurst parameter. The other statistics are within the confidence intervals. The CLR of the original traffic is significantly lower than the CLR of the modelled one reflecting the lack of correlation in the Pareto traffic.

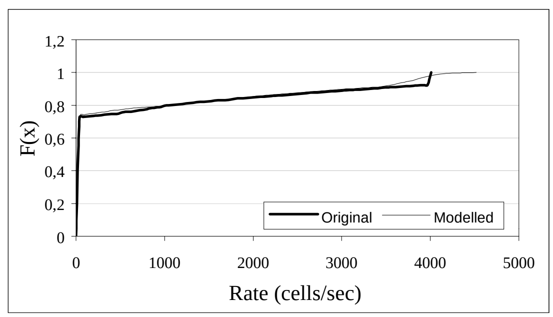


Figure 8: CDF for the IDP original traffic rate (darker) and modelled traffic rate .

The CMPP model can not match the value of the Hurst parameter of the Self-similar traffic. It was seen that the H.P. of the CMPP is always smaller than the H.P. of the original Self-similar traffic. The modelling process induces an increase in the variation of the arrival rate, Figure 10, as well as a higher auto-correlation, Figure 11. This shows that this modelling process may not be applied to Self-similar traffic with low rate variation.

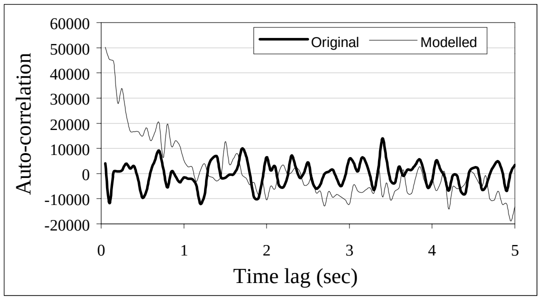


Figure 9: Auto-correlation function for the original Pareto traffic (darker) and modelled traffic.

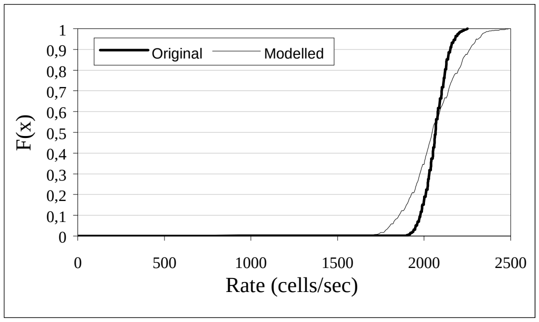


Figure 10: CDF for the original traffic rate with H=0.8 (darker) and modelled traffic rate.

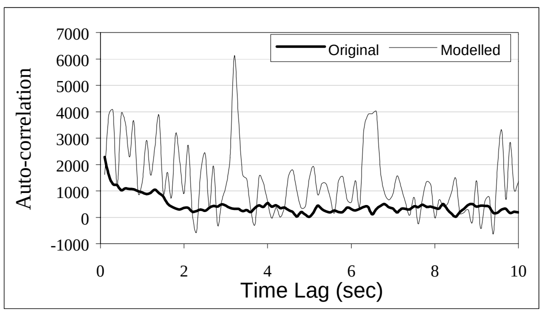


Figure 11: Auto-correlation function for the original self-similar traffic with H=0.8 (darker) and modelled traffic.

4. CONCLUSIONS

In this paper, we proposed and studied fitting algorithms for MMPP(2) and CMPP ATM traffic models, which are special cases of Markov Modulated Poisson Processes (MMPP). Two fitting algorithms, both based on the cell interarrival times, were considered for the MMPP(2) model: one fits the cumulative distribution and auto-covariance functions and other fits the first three moments and auto-covariance function. The fitting algorithm for the CMPP model is based on the cumulative distribution and auto-covariance functions of the arrival rate. The MMPP(2) was evaluated as a model for the superposition of IPP sources; the CMPP was evaluated as a model for MMPP(2), MMPP(3), MMPP(5), IPP, IDP, Pareto and Self-Similar traffic. The proposed algorithms were seen to be appropriate for the characterisation of ATM traffic streams and in connection admission control procedures.

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