Developing Standard Active Queue Management in MMPP

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Abstract: Access to the large web content in wide computer networks such as the Internet engages many hosts, routers/switches and faster links and they may challenge the internet backbone to operate at its capacity and this may result in congestion and raises concerns over various Quality of Service (QoS) issues like high delays, high packet loss and low throughput of the system for various Internet applications. Thus, there is a need to develop effective congestion control mechanisms to meet Quality of Service (QoS). In this paper, our emphasis is on the Active Queue Management (AQM) mechanisms, a new analytical approach based on 4-state Markov Modulated Poisson Process (MMPP) is introduced.
[Afshin Shaabany, Fatemeh Jamshidi. **Developing Standard Active Queue Management in MMPP.** Journal of American Science 2011;7(9):149-152]. (ISSN: 1545-1003). http://www.americanscience.org.

Keywords: AQM: Active Queue Management. MMPP: Markov Modulated Poisson Process. CT-MMPP: continues Time – MMPP.MQL: Mean Queue Length.

1. Introduction

Applications sensitive to quality of Service such as VOIP, IPTV and plays can come on an IP such as B-ISDN. These applications need distinctive quality of service and impose variety to the network. The application for bandwidth of network for an individual video service causes occupation of a major part of bandwidth in the network. A TV channel with a standard quality needs 2Mb/s bandwidth while a TV channel with higher quality allocates 6Mb/s to 10Mb/s of the network bandwidth. When application of multi-broadcast on the substructure improves the network, the increasing growth of number of channels and usage of TV networks keeps pressure on the substructure of the network capacity. [1]

Such requirements may cause high delays in providing data and lowering quality of service. Furthermore, applications and protocols used in networks including TCP, mostly, cause packet loss and low throughput as well as high delay of end to end in the network. The following table shows some of the requirements of quality of network for early applications and plays.

Table 1. quality requirements of network for various applications

APPLICATION	MAXIMUM ONEWAY DELAY	PACKET LOS IN THE NETWORK
IPTV	<100 msec	<0.01%
Video-n-Demand	<50 msec	<0.001%
VoIP	<150 msec	<0.1%
Video Conferencing	<150 msec	<0.05%
Gaming	<50 msec	<0.1%

Modeling of traffic resources and detecting parameters of quality of service provides critical steps for better understanding and solving problems of quality of service in switching packets of today and future. Therefore, to form a successful design for new networks, the most important outcome is the selection of proper traffic modeling for traffic resource to reflect traffic manner in the system.

2. Proposed Model

The Markov Modulated Poisson Process (MMPP) has been extensively used to model B-ISDN sources such as voice and video, as well as characterizing the superposed traffic. It captures the burstiness and correlation properties of the network traffic. In addition to characterizing the desired properties of B-ISDN applications, these models are analytically tractable and produce results that are acceptable approximations to reality. [2]

An MMPP is a doubly stochastic Poisson Process. The arrivals occur in a Poisson manner with a rate that varies according to a k-state Markov chain, which is independent of the arrival process. Accordingly, an MMPP is characterized by the transition rate matrix of its underlying Markov chain and arrival rates.

Let (i) be the state of the Markov chain (Q_{ij}) be the transition rate from

State (i) to state (j), ($i \neq j$) and i the arrival rate when the Markov chain is in state (i), ($i > 0$), and ($i \in \{g_2, \cdots, g_k\}$. Define:

$$\sigma_i = -\sum_{j=1;i\neq j}^{k} \sigma_{ik}$$

In matrix form, we have:

$$Q = \begin{bmatrix} -\sigma_1 & \sigma_{12} & \cdots & \sigma_{1k} \\ \sigma_{21} & -\sigma_2 & \cdots & \sigma_{2k} \\ \cdots & \cdots & \cdots & \cdots \\ \sigma_{k1} & \sigma_{k2} & \cdots & -\sigma_k \end{bmatrix} \quad \text{and}$$

$$A = \begin{bmatrix} \lambda_1 & 0 & \cdots & 0 \\ 0 & \lambda_2 & \cdots & 0 \\ \cdots & \cdots & \cdots & \cdots \\ 0 & 0 & \cdots & \lambda_k \end{bmatrix}$$

Assuming that Q does not depend on time t, the steady-state probability vector, (P), of Q is the solution of the following system of equations:

$$\pi Q = 0; \qquad \sum_{i=1}^{k} \pi_j = 1$$

In our model we use a pair of thresholds for each traffic class. Fig. 1 shows the positions of thresholds for two traffic classes, in a definite capacity buffer where traffic arrives using a 4-state Markov Modulated Poisson Process (MMPP) distribution. [1,2]

Figure. 1. Single buffer with two thresholds per traffic class.

We use a conventional matrices approach to solve four-dimensional CT-MMPP Markov chains. In order to do so we create a *Z* generator matrix based on a system state transition diagram comprising the input parameters (*¸ij):* arrival rate, (N): service rate, (*p = R):* Rate of transition from one state to the next state, and (*q = R'):* Rate of transition from second state to the first state.

Figure 2 shows the positions of thresholds and regions for the linear reduction in arrival rate.

Figure 2: Positions of thresholds and regions for the linear reduction in arrival rate.

We assume that $N_{21}\text{-}N_{11}=N_{22}\text{-}N_{12}$, such that $N_{12}\text{-}N_{11}=N_{22}\text{-}N_{21}$ and $N_{21} > N_{12}$.

The arrival rate (*¸ij)* are all independent of the state before N_{1i} or after N_{2i} and depend on the state between N_{1i} and N_{2i}, where $i = 1,2,3,4$, and $j = 0, 1, 2, \ldots, N$, *N* being full queue capacity. [3]

Each arrival rate is different with each state and will be linearly reduced by dropping packets in a region between thresholds N_{11}, N_{21}, and thresholds N_{12}, N_{22}, for first and second traffic class respectively. These arrival rates can be obtained as:

$$\lambda_{ij} = \begin{cases} \lambda_{1i}, \\ \text{for, } i = 1,2 \text{ and } 0 \le j \le N_{1i} \\ \lambda_j = \lambda_{1i} - (N_{1i} - j)\dfrac{\lambda_{2i} - \lambda_{1i}}{N_{2i} - N_{1i}} \\ \text{for, } i = 1,2 \text{ and } N_{1i} + 1 \le j \le N_{2i} \\ \lambda_{2i}, \\ \text{for, } i = 1,2 \text{ and } N_{2i} + 1 \le j \le N \end{cases}$$

In order to perform the steady state analysis of the system, we use the algorithm to solve the joint steady state probability vector P = P*j* (0· j·N) in the four-dimensional Markov chain, which satisfies the following equations:

PZ = 0 and Pe = 1

Where Z is the generator matrix based on the system state transition diagram. We have grouped states according to the total number of customers in the queue (where: *j* = states, and i = number of job class) and then we order states epigraphically, i.e. (1,0), (2,0), (1,1), (2,1), ... (1,N), where, *N* is the maximum queue length. Thus, the generator matrix Z is given by:

$$Z = \begin{pmatrix} A_{ij} & E_{ij} & 0 & 0 & . & . & . \\ C_{ij} & D_{ij} & E_{ij} & 0 & . & . & . \\ 0 & C_{ij} & D_{ij} & E_{ij} & 0 & . & . \\ . & . & . & . & . & . & . \\ . & . & . & . & . & . & . \\ . & . & . & . & . & C_{ij} & B_{ij} \end{pmatrix}$$

Where:

$$A_{ij} = \begin{bmatrix} -(p + \lambda_{ij}) & p \\ q & -q(q + \lambda_{ij}) \end{bmatrix}$$

$$B_{ij} = \begin{bmatrix} -(\mu + p) & p \\ q & -q(\mu + q) \end{bmatrix}$$

$$E_{ij} = \begin{bmatrix} \lambda_{ij} & 0 \\ 0 & \lambda_{ij} \end{bmatrix}, C_{ij} = \begin{bmatrix} \mu & 0 \\ 0 & \mu \end{bmatrix}$$

$$D_{ij} = \begin{bmatrix} -(\mu + p + \lambda_{ij}) & 0 \\ 0 & -(\mu + p + \lambda_{ij}) \end{bmatrix}$$

Solving the generator matrix Z yield the steady state vector as:

P = u (I ¡ Q + eu) ¡1 (4)

Where Q = I + Z/min*fZi;ig* and u is an arbitrary row vector of Q x I and e = (1, 1, . . . , 1) *T* is a unit column vector of length N. [4]

After the equilibrium probabilities P*j* are found, we can evaluate system performance metrics such as mean system occupancy, mean packet waiting time, system throughput and packet dropping probabilities. The average buffer occupancy or Mean Queue Length (MQL) can be expressed from the equilibrium probabilities P*j* as:

$$L = \sum_{j=0}^{N} jP_j$$

Using little's law; the delay for this definite capacity queue can be obtained as:

$$W = \frac{L}{S}$$

Where S is the mean throughput of the continuous time definite capacity queue given by the fraction of time the server is busy and is given as follows:

$$S = (1 - P_0) \times \beta$$

Similarly, we calculate the aggregate probability of packet Loss (as a measure of blocking probability) for the system by using the following relation:

$$P_B = \sum_j \left(1 - \tfrac{\lambda_j}{\lambda_2}\right) P(j) = \sum_j P(j) - \tfrac{1}{\lambda_1} \sum_j \lambda_j P(j)$$

$$\Rightarrow P_B = 1 - \tfrac{1}{\lambda_1} \sum_j \lambda_j P(j)$$

$$\Rightarrow P_B = 1 - \tfrac{1}{\lambda_1} \sum_j^j \lambda_j [P_{1_j} + P_{2_j}]$$

$$\Rightarrow P_B = 1 - \frac{\sum_{j=0}^{N} \sum_{i=1}^{2} \lambda_{ij} P_{ij}}{\sum_{i=1}^{2} \lambda_{1i}}$$

3. System Performance

Figures 3 and 4 present MQL and throughput against input parameters and threshold variations respectively. In our numerical examples for the fixed input parameters, we vary N12 and N22, where: N21 - N11= N22 - N12, and N12 - N11 = N22 - N21, such

That $N_{21} > N_{12}$. From the results it is clear that as we increase the threshold values, the mean queue length increases, which in turn increases the utilization of the system resulting in high throughput which is of the fact that even though the queue is accumulating packets, they are being served efficiently at the same time.

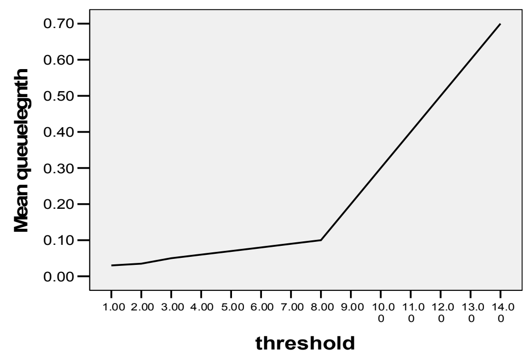

Fig. 3: Effects of Threshold on Mean Queue Length.

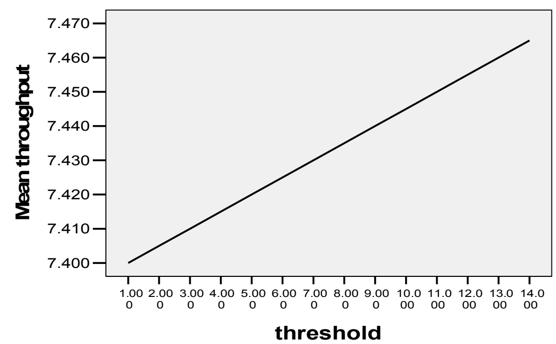

Fig. 4: Effect of Threshold on Throughput.

It is evident from results that the mean queue length can be maintained by setting the threshold value in order to prevent congestion. The Square Coefficient of Variation (SCV) is a measure of the variability associated with the inter-arrival and processing times of the system.The variation in SCV value, which is a function of arrival rate and transition probability in each state, greatly affects the performance of a switch/router and is an important measure of the degree of traffic burstiness in the CT-MMPP traffic source.

In our model, the SCV, *c*2, of the inter-arrival time of a four-state CT-MMPP for the packets arrival process is given by the following expression:

$$c^2 = 1 - \frac{2pq(\lambda_1 - \lambda_2)^2}{(q\lambda_1 + p\lambda_2 + \lambda_1\lambda_p)(p+q)^2}$$

The autocorrelation coefficient of the inter-arrival times and the number of arrivals are the two important measures of interest. The autocorrelation function of the inter-arrival time of packets with lag 1, C (1), is given by:

$$C(1) = \frac{\lambda_1\lambda_2(\lambda_1 - \lambda_2)pq}{c^2\{p+q\}^2\{\lambda_1\lambda_2 + \lambda_1 q + \lambda_2 p\}^2}$$

Figure 5 shows the effect of load variation (input arrival rate) on SCV of inter-arrival times.

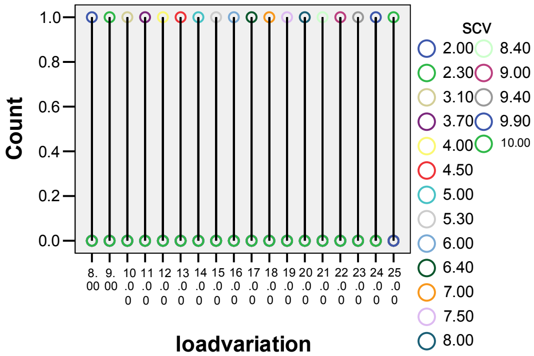

Fig. 5: Effects of load variation on SCV.

The higher burstiness traffic causes higher system MQL and higher throughput for the same threshold based on this assumption that the traffic is unchangeable.

4. Conclusion and Future Work:

A novel approximate analytical performance model of a multiple threshold congestion control mechanism for implementing the AQM scheme is presented in this paper. Furthermore, the analysis of definite capacity queue based on four-state CT-MMPP distribution has been proposed to model the bursty Internet traffic. The traffic source slows down the arrival process once the queue size reaches the maximum threshold, jobs are blocked. Different job loss and QoS requirements under various load conditions can be met by adjusting the threshold values. Also, the effect of threshold based queue on correlated traffic scenarios by introducing correlation to our CT-MMPP model of bursty traffic is demonstrated. Typical numerical examples are included to demonstrate the effects of threshold variation on QoS measures and correlation function of a system.

For further research and improving the proposed model in a simulator environment containing real-time 3G traffic as an input source and evaluating its impact on QoS measures.

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References

1. Stirilng G, Wilsey B. Emprical relationships between species richness, eveness and proporational diversity. Am Nat 2001;158(3):286-99.
2. Smith MD, Wilcox JC, Kelly T, Knapp AK. Dominance not richness determines invasibility of tallgrass prairie. Oikos 2004;106(2):253–62.
3. Gaston K J. Global pattern in biodiversity. Nature 2000;405(1):220-7.
4. Tilman D. Causes, consequences and ethics of biodiversity. Nature 2000;405(4):208-11.
5. Brown J. Mammals on mountainsides: elevational patterns of diversity. Global Ecology and Biogeography 2001;10(1):101-9.
6. Sanders NJ, Moss J, Wagner D. Pattern of ant species richness along elevational gradients in an arid ecosystem. Global Ecology and Biogeography 2003;10(2):77-100.
7. Grytnes JA, Vetaas OR. Species richness and altitude: A comparison between null models and interpolated plant species richness along the Himalayan altitudinal gradient, Nepal. The Am Nat 2002;159(3):294-304.
8. Singh JS, Singh SP. Forest vegetation of the Himalaya. Bot Rev 1987;52(2):80-192.
9. Rawat YS, Singh JS. Forest floor, litter falls, nutrient return in central Himalayan forests. Vegetatio, 1989;82(2):113-29.
10. Singh JS, Singh SP. Forest of Himalaya: Structure, Functioning and Impact of man. Gyanodaya Prakashan, Nainital, India, 1992.
11. Valida KS. Geology of Kumaun lesser Himalaya, Wadia Institute of Himalaya Geology, Dehradun, India, 1980;291.
12. Shannon CE, Wienner W. The mathematical theory of communication. Univ. Illinois Press, Urbana, 1963.
13. Simpson EH. Measurement of Diversity. Nature 1949;163(2):688-91.
14. Whittaker RH. Community and Ecosystems. IInd ed. McMillan, New York, 1975.
15. Whittaker RH. Evolution and measurement of species diversity. Taxon 1972;21:213-51.
16. Saxena AK, Pandey P, Singh JS. Biological Spectrum and other structural functional attributes of the vegetation of Kumaun Himalaya, Vegetatio 1982;49(1):111-9.
17. Mehrotra P. Adaptive significance of leaf in relation to other parts in oak forest herbs of Kumaun Himalaya, Ph. D. Thesis, Kumaun University, Nainital, India, 1988.
18. Moustafa AA. Environmental Gradient and Species Distribution on Sinai Mountains. Ph. D. Thesis, Botany Department, Faculty of Science, Suez Canal University, Egypt, 1990;115.
19. Tewari JC. Vegetational analysis along altitudinal gradients around Nainital, Ph. D. Thesis, Kumaun University, Nainital, 1982;570.
20. Pielou EC. Ecological Diversity. Wiley, New York, 1975;165.
21. Magurran AE. Ecological Diversity and Its Measurement. Princeton University Press, Princeton, New Jersey, 1988;179.

6/18/2011