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Performance Analysis of Active Queue Management Scheme for Bursty and Correlated Multi-Class Traffic

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Abstract: With the rapid growth of Internet traffic, the control of congestion to enable different types of Internet traffic to satisfy specified Quality of Service (QoS) constraints is becoming increasingly important. This motivates the stochastic analysis of a discrete-time queueing system for the performance evaluation of active queue management (AQM) scheme based congestion control mechanism called Random Early Detection (RED) with bursty and correlated traffic using a two-state Markov-Modulated Bernoulli arrival process (MMBP-2) as the traffic source. The stochastic analysis of the queue considered could be of interest for the performance evaluation of AQM for the multiple-class traffic with short range dependent (SRD) traffic characteristics. Analytical expressions for various performance metrics are computed and typical numerical experiments are included to illustrate the credibility of the proposed mechanism in the context of external bursty and correlated traffic. These experiments clearly demonstrate how different threshold settings can provide different tradeoffs between loss probability and delay to suit different service requirements. The effect of input parameters on various performance metrics, burstiness and correlations for the arrival process are also presented. The model is applicable to high speed networks which use slotted protocols.

Keywords: Queueing Theory, Queue Thresholds, Congestion Control, MMBP-2, AQM, RED, Quality of Service (QoS)

1 INTRODUCTION

With the rapid development of the Internet, the control of congestion has become one of the most critical issues in present networks to accommodate the increasingly diverse range of services and types of traffic [1]. Congestion control to enable different types of Internet traffic to satisfy specified Quality of Service (QoS) constraints is becoming significantly important. Many systems in network environments require the queue to be monitored for impending congestion before it happens [2].

The traditional technique for managing router queue lengths is to set a maximum length for each queue, usually equal to the buffer capacity, and then accept packets until the queue becomes full. The subsequent arrivals will be blocked until some space becomes available in the queue as a result of departures. This technique is known as “tail drop”, since the packet that arrived most recently (i.e., the one on the tail of the queue) is dropped when the queue is full. This method has been used for several years in the Internet, but it has two important drawbacks: ‘Lock-Out’ and ‘Full Queues’ [3]. In order to solve the problems, some active queue management (AQM) mechanisms have been proposed and implemented to manage the queue lengths, reduce end-to-end latency, reduce packet dropping and avoid lock-out phenomena so that the control of congestion can be achieved by the use of appropriate buffer management schemes. These mechanisms include random early detection (RED) [4], random early marking (REM) [5, 6], a virtual queue based scheme where the virtual queue is adaptive [7, 8, 9] and a proportional integral controller mechanism [10], among others. Of these schemes to implement AQM, RED is the default mechanism, recommended by the Internet Society in RFC 2309 [3] for managing queue lengths to meet these goals in a first-come first-out (FIFO) queue.

In contrast to tail drop, RED [4] drops arriving packets probabilistically depending on setting thresholds in the queue. When the average queue length is less than a minimum threshold, all incoming packets are allowed to the queue. If the mean queue length is greater than a maximum threshold, every arriving packet is dropped. Between the minimum and maximum thresholds, incoming packets are dropped with a probability that increases linearly as a function of the mean queue length, reaching a maximum dropping probability at the maximum threshold.

Since RED was proposed by Floyd and Jacobson [4] in 1993, most researchers have used simulation tools as the choice of modelling to examine the performance of various aspects of the RED algorithm. Only a few publications, (e.g., [11-14]) have attempted to theoretically evaluate the performance of RED. To the authors’ knowledge, there is no clear description of the parameter settings and exact information being measured. Therefore, it is very important and necessary to use an analytical approach to address the more fundamental aspects of the RED based algorithm. This paper proposes a new analytical framework for the RED based algorithm that takes into account the reduction in incoming traffic arrival rate due to packets dropped probabilistically with the drop probability increasing linearly with system contents. More specifically, this paper presents a discrete-time finite capacity queue with two traffic classes using MMBP-2 traffic arrival process for the performance evaluation of congestion control mechanism based on the RED algorithm using queue thresholds which incorporates a two-dimensional discrete-time Markov chain (each dimension corresponding to a traffic class with its own RED parameters) which captures the feedback effect of dropping packets on the incoming traffic. The stochastic analysis of the queue considered could be of interest

the chain-one (or BL_2 in the chain-two). Let the probability of a departure in a slot be β. When the number of packets in the system is between the first threshold and the second threshold, the arrival rate will be linearly reduced with some probability which is the function of α_1, α_3 (or α_2, α_4) and the two thresholds. The dropping probability increases linearly from 0 to the maximum $1-\alpha_3/\alpha_1$ (or $1-\alpha_4/\alpha_2$). This can be considered as implicit feedback from queue to the arrival process in that dropping packets reduces the effective arrival rate into the queue from α_1 to $\alpha_1- \alpha_3$ (or from α_2 to $\alpha_2- \alpha_4$) with a linear reduction. We assume that the queueing system is in equilibrium state. The state transition diagram is shown in Fig. 2, and the queue length process is a two-dimensional discrete-time Markov chain with a finite state space $\{1, 2\}\times\{0, 1, \ldots, N\}$.

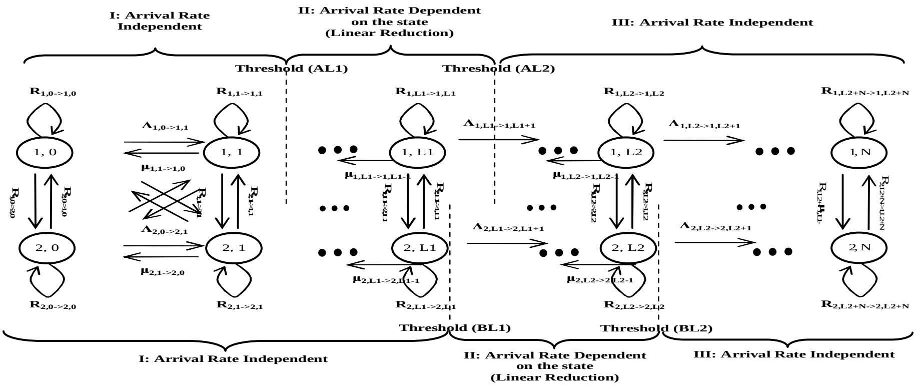

Fig.2 State transition diagram of the two-dimensional discrete-time Markov chain with two thresholds in the different position of each chain (AL_1, AL_2 in the chain-one and BL_1, BL_2 in the chain-two)

As shown in Fig. 2, the arrival rate α_1 (or α_2) in part I and α_3 (or α_4) in part III are independent of the states before AL_1 (or BL_1) and AL_2 (or BL_2). However, between two thresholds (AL_1 and AL_2 or BL_1 and BL_2--Part II) in each chain, the arrival rates depend on the states i.e., each arrival rate is different in each state and will be linearly reduced by dropping packets. We assume that $\alpha_i \neq \beta$ ($1\leq i\leq 4$) and the final state N is the full buffer situation.

2.2 Performance Analysis

To find the steady state probability distribution, the transition probabilities of arrivals, departures and remaining in the same state for the two-dimensional Markov chain with two thresholds in the different position of each chain can be defined

where **Z** is the transition probability matrix consisting of three vectors $[\mathbf{\Lambda}]_{(i,j)\text{->}(i',j')}$, $[\boldsymbol{\mu}]_{(i,j)\text{->}(i',j')}$ and $[\mathbf{R}]_{(i,j)\text{->}(i',j')}$ and $\mathbf{e} = (1, 1, \ldots, 1)^T$ is a unit column vector of length N. Solving these equations yields the steady state vector as in [17]

$$\mathbf{P} = \mathbf{u}\,(\mathbf{I} - \mathbf{Q} + \mathbf{eu})^{-1} \tag{5}$$

where $\mathbf{Q} = \mathbf{I} + \mathbf{Z}/\min\{\mathbf{Z}_{i,i}\}$, **u** is an arbitrary row vector of **Q** and **I** is a N× N identity matrix.

Once the equilibrium probabilities $\mathbf{P}_i$ ($0\le i \le N$) are solved, we can evaluate the system performance metrics (aggregate and marginal per class) for mean system occupancy, mean packet waiting time, system throughput and packet dropping probabilities.

The aggregate mean buffer occupancy can be expressed from the equilibrium joint probabilities $\mathbf{P}_i$:

$$L = \sum_{i=0}^{N} i\mathrm{P}_i \tag{6}$$

The overall mean delay can be obtained from Little's law for this finite capacity queue as:

$$W = \frac{L}{S} \tag{7}$$

where S is the mean throughput of the discrete-time finite capacity queue given by the fraction of time the server is busy:

$$S = (1 - \mathrm{P}_0) \times \beta \tag{8}$$

The total loss probability D_L is the sum of each traffic class loss probability, which is given by

$$D_L = D_{L1} + D_{L2} \tag{9}$$

where D_{L1} and D_{L2} are the probability of packet loss for traffic class1 and class2 respectively:

$$D_{L1} = \sum_{j=L_1}^{L_2-1} P_{1j} D_{1j} + D_3 \sum_{j=L_2}^{N-1} P_{1j} + P_{1N}\left[\beta D_3 + (1-\beta)\right] \tag{9a}$$

$$D_{L2} = \sum_{j=L_1}^{L_2-1} P_{2j} D_{2j} + D_4 \sum_{j=L_2}^{N-1} P_{2j} + P_{2N}\left[\beta D_4 + (1-\beta)\right] \tag{9b}$$

where

$$D_{ij} = 1 - \frac{\alpha_{ij}}{\alpha_i}, \quad i = 1, AL_1 \le j \le AL_2 - 1 \;\; or \;\; i = 2, BL_1 \le j \le BL_2 - 1$$

$$D_i = 1 - \frac{\alpha_i}{\alpha_{i-2}}, \quad i = 3, AL_2 \le j \le N \;\; or \;\; i = 4, BL_2 \le j \le N$$

and the joint probabilities, $\mathbf{P}_i$, are the sum of the marginal probability in each state in

Fig. 3 indicates the values of marginal delay for class1 is lower than class2 for the same threshold settings where AL_1=3 and AL_2=7 are fixed values, as to be expected, since the two thresholds of class 2 moving backwards to the end of the queue (BL_1 or BL_2 varies over a given range). This figure also indicates the lower marginal delay in each class can be achieved by using a narrow separation of the same thresholds in the two classes (BL_1-AL_1 or BL_2-AL_2). However, Fig. 4 shows the values of marginal loss probability for class 2 is lower than class1 for the same threshold settings and the lower loss probability for class2 can be achieved by using a wide separation of the same thresholds in the two classes (BL_1-AL_1 or BL_2-AL_2). Note the distance between two thresholds in each class ((AL_2-AL_1 or BL_2-BL_1) also affects the marginal delay and loss probability.

3.2 Effect of Traffic Burstiness

This section demonstrates the effect of traffic burstiness upon the system performance using various values of the Squared Coefficient of Variation (SCV). The SCV, of the interarrival times of the packets for the arrival process (a function of arrival rate and transition probability in each phase) is an important measure of the degree of traffic burtiness in the MMBP-2 traffic source. A higher value of c^2 can be achieved by using a higher value of transition probabilities p and q (e.g., p, q=0.9999), and a large value of $|\alpha_1 - \alpha_2|$.

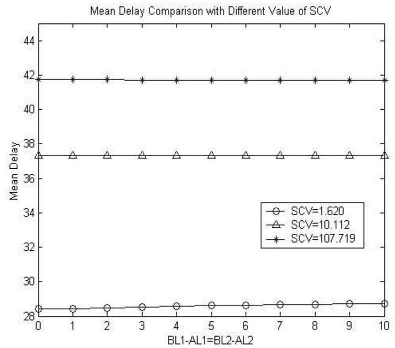

Fig. 5 Mean delay vs. BL_1-AL_1

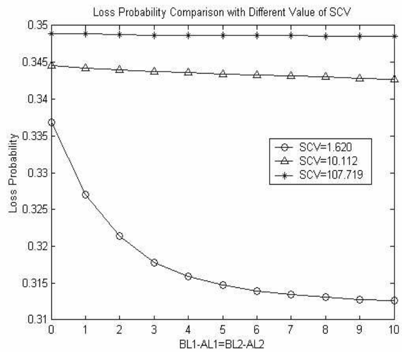

Fig.6 Loss probability vs. BL_1-AL_1

The numerical results of overall mean delay and loss probability with different value of SCV (SCV=1.620, 10.112, 107.719) are compared in Figs. 5 and 6 respectively. The value of SCV can be changed while the input load remains constant. These results have been obtained by keeping the mean arrival rate, α, constant at 0.5 ($\alpha = \alpha_1 P(1) + \alpha_2 P(2)$) and specific value P(1)=P(2)=0.5 and p=q=0.9999 (these values of p and q give higher value of SCV). The SCV (SCV=1.620, 10.112, 107.719) is changed by changing α_1 =0.8, 0.955, 0.9955, α_2 =0.2, 0.045, 0.0045. Figs. 5-6 show that the higher burstiness traffic causes higher

of incoming traffic arrival rate due to packets dropped probabilistically with the drop probability increasing linearly with system contents. The analysis is easy to apply and provides insight into the performance of RED algorithm in a wide variety of situations. The performance evaluation of the proposed analytical model enables the best threshold settings and drop probability to be chosen to suit the type of service required; i.e., to give an appropriate trade-off between delay and packet loss probability. For example, real-time services require low delay, while data services require low packet loss. It has also been demonstrated that the model can capture the effects on performance of both burstiness and correlations in the arrival process and hence lend itself to model traffic with SRD characteristics.

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