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
for the performance evaluation of RED based mechanism for multi-class traffic with SRD traffic characteristics.

The remainder of the paper is organised as follows: The discrete-time system model with two traffic classes is described in Section 2 including performance parameter measurements. The performance evaluation of the proposed model is presented through typical numerical results in Section 3. Finally, the conclusions and suggestion for future work follow in Section 4.

2 SYSTEM PERFORMANCE ANALYSIS

This section presents the description of the proposed model and analytical expressions for various performance metrics.

2.1 System Description

This section introduces the system theoretical framework based on RED algorithm and presents the formulation of the analytical model in a discrete-time finite capacity queue with two thresholds in each dimensional Markov chain which corresponding to each traffic class with its own RED parameters. This analysis is based on a departure first buffer management scheme where a departure always takes place before an arrival in any unit time (slot). Arrivals form a MMBP-2 to a finite waiting room of N packets, including any in service, with two thresholds in the different position of each dimensional Markov chain, namely, \( \{AL_1, AL_2\} \) in chain-one and \( \{BL_1, BL_2\} \) in chain-two (c.f., Fig. 1). The packets are served according to first-in first-out (FIFO) service discipline. For analysis purposes, the queueing system state has been defined as the instantaneous queue length, as in [11, 12].

![Fig.1](image)

Fig.1 Single buffer with two thresholds in each dimensional Markov chain \( (AL_1, AL_2 \text{ and } BL_1, BL_2) \)

Let the probability of an arrival in a slot be \( \alpha_1 \) when the arrival process in state-one (or be \( \alpha_2 \) when the arrival process in state-two) before the number of packets in the system reaches the first threshold \( AL_1 \) in the chain-one (or \( BL_1 \) in the chain-two). Let the probability of an arrival in a slot be reduced to \( \alpha_3 \) in state-one (or \( \alpha_4 \) in state-two) after the number of packets in the system reaches the second threshold \( AL_2 \) in
the chain-one (or BL2 in the chain-two). Let the probability of a departure in a slot be \( \beta \). 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 \( \alpha_1, \alpha_3 \) (or \( \alpha_2, \alpha_4 \)) 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 \( \alpha_1 \) to \( \alpha_1-\alpha_3 \) (or from \( \alpha_2 \) 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 \( \{1, 2\} \times \{0, 1, \ldots, N\} \).

As shown in Fig. 2, the arrival rate \( \alpha_1 \) (or \( \alpha_2 \)) in part I and \( \alpha_3 \) (or \( \alpha_4 \)) in part III are independent of the states before \( \text{AL}_1 \) (or \( \text{BL}_1 \)) and \( \text{AL}_2 \) (or \( \text{BL}_2 \)). However, between two thresholds (\( \text{AL}_1 \) and \( \text{AL}_2 \) or \( \text{BL}_1 \) and \( \text{BL}_2 \)--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.
using vectors $[\Lambda]_{(i,j) \to (i',j')}$, $[\mu]_{(i,j) \to (i',j')}$ and $[R]_{(i,j) \to (i',j')}$ respectively, where $i$ and $j$ represent the transition states (c.f., Fig 3).

- **Transition probabilities of arrivals**

$[\Lambda]_{(i,j) \to (i',j')}$ represents the transition probabilities of arrivals in the two dimensional Markov chain and is defined as:

$$
[\Lambda]_{(i,j) \to (i',j')} = \begin{cases} 
\Lambda_{i} \alpha_j, & i = 1,2 \text{ and } 0 \leq j \leq N \\
\Lambda_{i+1} \alpha_j, & i = 1 \text{ and } 0 \leq j \leq N \\
\Lambda_{i-1} \alpha_j, & i = 2 \text{ and } 0 \leq j \leq N 
\end{cases} \tag{1}
$$

where the three elements can be expressed as the functions of input parameters $\alpha$, $\beta$, $p$ and $q$:

$$
[\Lambda]_{(i,j) \to (i,j+1)} = \begin{cases} 
\alpha_i p, & i = 1 \text{ and } j = 0 \\
\alpha_j (1 - \beta)p, & i = 1 \text{ and } 1 \leq j \leq N \\
\alpha_i q, & i = 2 \text{ and } j = 0 \\
\alpha_j (1 - \beta)q, & i = 2 \text{ and } 1 \leq j \leq N 
\end{cases} \tag{2a}
$$

$$
[\Lambda]_{(i,j) \to (i+1,j+1)} = \begin{cases} 
\alpha_i (1 - p), & i = 1 \text{ and } j = 0 \\
\alpha_j (1 - \beta)(1 - p), & i = 1 \text{ and } 1 \leq j \leq N 
\end{cases} \tag{2b}
$$

$$
[\Lambda]_{(i,j) \to (i-1,j+1)} = \begin{cases} 
\alpha_i (1 - q), & i = 2 \text{ and } j = 0 \\
\alpha_j (1 - \beta)(1 - q), & i = 2 \text{ and } 1 \leq j \leq N 
\end{cases} \tag{2c}
$$

The transition probabilities for departure $[\mu]_{(i,j) \to (i',j')}$ and remaining in the same state $[R]_{(i,j) \to (i',j')}$ can be obtained in the similar way.

From these equations, the arrival rate $\alpha_{ij}$ can be obtained as below:

$$
\alpha_{ij} = \begin{cases} 
\alpha_i, & i = 1, 0 \leq j \leq AL_i - 1 \text{ or } i = 2, 0 \leq j \leq BL_i - 1 \\
\alpha_i (j - AL_i + 1) \frac{\alpha_i - \alpha_{i+1}}{AL_i - AL_i + 1}, & i = 1, AL_i \leq j \leq AL_i - 1 \\
\alpha_i (j - BL_i + 1) \frac{\alpha_i - \alpha_{i+1}}{BL_i - BL_i + 1}, & i = 2, BL_i \leq j \leq BL_i - 1 \\
\alpha_i, & i = 1, AL_i \leq j \leq N \text{ or } i = 2, BL_i \leq j \leq N 
\end{cases} \tag{3}
$$

In order to perform the steady state analysis of the system, we use algorithms in [17] to solve the joint steady state probability vector $P = P_i \ (0 \leq i \leq N)$ in the two-dimensional Markov chain, which satisfies the following equations

$$
P Z = 0 \quad \text{and} \quad P e = 1 \tag{4}
$$
where $Z$ is the transition probability matrix consisting of three vectors $[A]_{(i,j)\rightarrow(i',j')}$, $[\mu]_{(i,j)\rightarrow(i',j')}$ and $[R]_{(i,j)\rightarrow(i',j')}$ and $e = (1, 1, \ldots, 1)^T$ is a unit column vector of length $N$. Solving these equations yields the steady state vector as in [17]

$$P = u (I - Q + eu)^{-1}$$

(5)

where $Q = I + Z/\min\{Z_{ii}\}$, $u$ is an arbitrary row vector of $Q$ and $I$ is a $N \times N$ identity matrix.

Once the equilibrium probabilities $P_i$ ($0 \leq i \leq N$) 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 $P_i$:

$$L = \sum_{i=0}^{N} iP_i$$

(6)

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

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

(7)

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

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

(8)

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

$$D_L = D_{L1} + D_{L2}$$

(9)

where $D_{L1}$ and $D_{L2}$ are the probability of packet loss for traffic class 1 and class 2 respectively:

$$D_{L1} = \sum_{j=L_4}^{L_1-1} P_{1j} D_{1j} + D_3 \sum_{j=L_3}^{N-1} P_{1j} + P_{1N} \left[ \beta D_4 + (1 - \beta) \right]$$

(9a)

$$D_{L2} = \sum_{j=L_4}^{L_1-1} P_{2j} D_{2j} + D_4 \sum_{j=L_3}^{N-1} P_{2j} + P_{2N} \left[ \beta D_4 + (1 - \beta) \right]$$

(9b)

where

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

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

and the joint probabilities, $P_i$, are the sum of the marginal probability in each state in
the two-dimensional Markov chain, which is given by 
\[ P_i = P_j + P_{(j+1)i}, \quad \text{for } j=1,2, \ 0 \leq i \leq N. \]

Similarly, the marginal delay for each class can also be obtained through Little’s law:
\[ W_1 = \frac{L}{S_1}, \quad W_2 = \frac{L}{S_2} \tag{10} \]
where \( S_1 \) and \( S_2 \) are the different fraction of the overall throughput for class 1 and class 2 traffic:
\[ S_1 = \alpha_1 P(1) (1 - D_{L_1}) \tag{11a} \]
\[ S_2 = \alpha_2 P(2) (1 - D_{L_2}) \tag{11b} \]
where \( P(1) \) and \( P(2) \) are the steady state probabilities shown in the equation (2)-(3).

3 NUMERICAL RESULTS

This section presents typical numerical results to demonstrate the credibility of the proposed analytical solution subject to various parameter settings. These examples focus on evaluation of comparison analysis of marginal delay and loss probability between two traffic classes; the effects of traffic burstiness and the impact of traffic correlation upon various performance measures.

3.1 System Performance

• Marginal Delay and Loss Probability Comparison Between Two Traffic Classes

Using the equations (9a), (9b) and (15), Figs 3-4 show the comparison results of marginal delay and loss probability between two traffic classes against BL\(_1\)-AL\(_1\) (=BL\(_2\)-AL\(_2\)) respectively, where AL\(_1\)=3, and the other input parameter values are the same as the last section.

![Fig.3 Marginal Delay Comparison between Two Classes (L)](image)

![Fig.4 Marginal Loss Probability Comparison between Two Classes (R)](image)
Fig. 3 indicates the values of marginal delay for class 1 is lower than class 2 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 class 1 for the same threshold settings and the lower loss probability for class 2 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 burstiness 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 $|\alpha_1 - \alpha_2|$.

![Mean delay vs. BL$_1$-AL$_1$](image1)

![Loss probability vs. BL$_1$-AL$_1$](image2)

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, $\alpha$, constant at 0.5 ($\alpha = \alpha_1P(1) + \alpha_2P(2)$) 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 $\alpha_1 = 0.8$, 0.955, 0.9955, $\alpha_2 = 0.2$, 0.045, 0.0045. Figs. 5-6 show that the higher burstiness traffic causes higher
system mean delay and also higher loss probability for the same threshold settings based on the assumption that the total amount of the traffic remains constant.

3.3 Autocorrelation Coefficient

The autocorrelation coefficient for the interarrival time (CI) is a very important parameter to measure the degree of traffic correlation. This correlation parameter is the functions of arrival rate and transition probability in each phase of the MMBP-2 traffic arrival process. A higher value CI can be achieved by using higher values of transition probabilities \((p, q)\) along with higher absolute value of subtraction of two arrival rates, \(|\alpha_1 - \alpha_2|\), whereas CI subject to the lower value of SCV.

- **Autocorrelation Function of the Interarrival Time (CI)**

The numerical results of mean delay and loss probability with different values of CI with lag 1 (CI=0.004, 0.157, 0.474) are compared in Figs. 7 and 8, respectively. These have been obtained by keeping the mean arrival rate, \(\alpha\), constant at 0.5 (\(\alpha = \alpha_1 P(1) + \alpha_2 P(2)\)) and specific value \(P(1)=P(2)=0.5\). The CI (CI=0.004, 0.157, 0.474) is changed by changing \(\alpha_1 = 0.8, 0.8, 0.955, \alpha_2 = 0.2, 0.2, 0.045, p=q=0.4, 0.9, 0.9999\). Figs. 7-8 show the higher values of CI cause higher system mean delay and higher loss probability for the same threshold settings.

4 CONCLUSIONS

This paper presents stochastic analysis of a discrete-time queue with multi-class bursty and correlated external traffic as an effective performance evaluation tool for the Internet traffic congestion control. The analysis is based on the RED mechanism with two thresholds for each traffic class. The arrival process is based on the theory of two-dimensional discrete-time Markov chains to model two traffic classes by using an MMBP-2 arrival process (each dimension corresponds to a traffic class with its own parameters). This process takes into account the reduction
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.

REFERENCES