Received: May 22, 2024. Revised: June 13, 2024.

International Journal of
Intelligent Engineering & Systems

http://www.inass.org/

A New Framework for Evaluating Random Early Detection Using Markov Modulate Bernoulli Process Stationary Distribution

Ahmad Adel Abu-Shareha[1]* **Mosleh M. Abualhaj[2]** **Mohammad A. Alsharaiah[1]**
Qusai Y. Shambour[3] **Adeeb Al-Saaidah[2]**

[1]*Department of Data Science and Artificial Intelligence, Al-Ahliyya Amman University, Amman, 19328, Jordan*
[2]*Department of Networks and Cybersecurity, Al-Ahliyya Amman University, Amman, 19328, Jordan*
[3]*Department of Software Engineering, Al-Ahliyya Amman University, Amman, 19328, Jordan*
* Corresponding author's Email: a.abushareha@ammanu.edu.jo

Abstract: Traffic modeling is crucial for designing and evaluating active queue management (AQM) methods used in network routers to control congestion. The Bernoulli process (BP), commonly used to model the traffic, falls short in capturing the burstiness of Internet traffic. Besides, the Markov Modulated Bernoulli Process (MMBP) with multiple states and varying probabilities allows the determination of each state's load independently but does not set specific overall traffic loads. This limitation hinders the establishment of a baseline for evaluating AQM methods. To address these issues, this paper introduces an enhanced traffic modeling approach using the stationary distribution of the Markov Modulated Bernoulli Process (MMBP-SD). This new model calculates the stationary distribution to match the required traffic load while varying its burstiness, enabling a fair comparison with the Bernoulli process of a predefined traffic load and facilitating the assessment of AQM behaviors. The proposed approach was tested under various traffic loads and evaluated using the burstiness factor (BF) and the maximum burstiness duration (MBD). The results showed that the MMBP-SD improved the BF by 6.2% and the MBD by 118% compared to the BP. Evaluating Random Early Detection (RED) was conducted using MMBP-SD and based on delay, loss, and packet dropping. This evaluation revealed that the RED performance in terms of packet loss degrades when using a 4-state MMBP-SD (e.g., packet loss increased by 28.5%) as RED maintains the same dropping rate as in the single-state model, highlighting a limitation of the RED method.

Keywords: Markov modulated Bernoulli process, Random early detection, Traffic modeling, Congestion control.

1. Introduction

Managing network congestion is a significant challenge in computer networking, where continuous and efficient data transmission is essential. As data traffic nears network capacity limits, effective congestion control mechanisms become increasingly critical. Active Queue Management (AQM) is a key solution in this context. AQM employs proactive techniques and algorithms within network routers to regulate data packet flow, especially during high traffic load and congestion. The primary goal of AQM is to balance efficient network utilization with the prevention of congestion, which can degrade overall network performance. AQM accomplishes this by actively monitoring network traffic and queue lengths within buffers, dynamically discarding or marking packets to prevent packet loss and excessive queuing delays [1].

The Random Early Detection (RED) algorithm stands out as a pioneering and widely utilized method for Active Queue Management (AQM). By continuously monitoring the length of the queue, RED offers early indications of potential network congestion. Unlike conventional drop-tail mechanisms that only discard packets when the queue is fully occupied, RED takes a proactive stance. RED employs stochastic packet drops as the queue length increases, thereby acting before the queue reaches its maximum capacity. This approach effectively mitigates the risk of abrupt congestion and substantially lowers packet loss, enhancing network stability and overall quality of service [2].

The packet-dropping mechanism in RED is governed by a dropping probability (Dp) parameter, calculated based on the average queue length and specific thresholds. This mechanism stochastically signals data sources to adjust their transmission rates once the average queue length surpasses these thresholds. RED's ability to forecast congestion trends and adjust to dynamic network conditions makes it a crucial tool in modern network management [3].

However, one notable challenge with RED is its sensitivity to parameter configuration, often leading to an elevated packet-dropping rate [4]. Furthermore, RED's dependence on the average queue length (AQL) as an indicator for packet dropping may not always accurately reflect imminent congestion. These limitations are particularly evident when RED is paired with the Bernoulli traffic model in simulations. With its simplistic and idealized representation of traffic patterns, the Bernoulli traffic model fails to capture the complexities of real-world network traffic [5].

Traffic modeling is crucial for Active Queue Management (AQM) methods, influencing their behavior. Two widely used techniques for traffic modeling are the Bernoulli Process (BP) and the Markov Modulated Bernoulli Process (MMBP), often employed with AQM methods like RED. The BP is a fundamental stochastic model that describes packet arrivals in a network, where events occur randomly and independently at a constant rate λ. While the BP can capture basic traffic characteristics and specific load rates, it fails to represent the complexity of real-world network traffic, which often exhibits variations in arrival rates [6].

The MMBP incorporates a Markov chain to address the BP limitations, introducing complexity into the traffic generation probability. In the MMBP, the packet arrival probability varies according to the state of the underlying Markov chain. This allows the MMBP to model traffic with varying characteristics over time, providing a more realistic representation of network behavior. The variability in probabilities is particularly useful for capturing traffic patterns transmitted between different states, such as bursty and non-bursty periods. However, it does not allow for setting a precise traffic load, as different states correspond to different load rates [7]. These models are represented as given in Fig. 1.

Combining the ability to generate variable load with a predefined rate can be implemented using the stationary distribution of the Markov model (MMBP-SD), as proposed in this paper. MMBP's ability to model diverse traffic characteristics aligns seamlessly with the AQM goal of proactive congestion management. Additionally, MMBP facilitates a more effective and adaptable AQM design by configuring AQM methods to dynamically adjust their behavior based on the traffic patterns modeled by MMBP. MMBP-SD addresses the limitation in network simulation of imprecise load, resulting in relatively undefined arrival probability modeling.

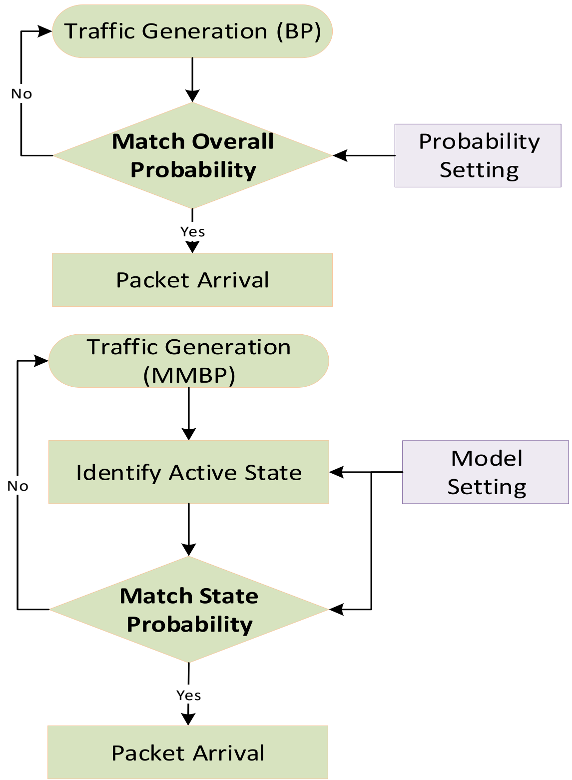


Figure. 1 Traffic modeling using BB and MMBP

This paper introduces a novel approach to traffic modeling using MMBP-SD and employs it to assess the performance of RED compared to BP. The key contributions of this work are outlined as follows: 1) Propose a traffic model grounded in the stationary distribution of the MMBP. 2) Demonstrate the feasibility and accuracy of the MMBP-SD by evaluating the generated model to validate the MMBP-SD concept. 3) Evaluate the RED's performance using the MMBP-SD and BP models.

The proposed MMBP-SD model offers new features over traditional traffic models. Firstly, it accurately captures traffic's burstiness, which is crucial for realistic performance evaluations of AQM methods. Secondly, the model allows for a predefined overall traffic load while varying burstiness, enabling fair and comprehensive comparisons with conventional models such as BP. The main advantages include a better representation of real-world traffic dynamics and improved evaluation of RED's performance under diverse traffic conditions. The model will be evaluated based on its brustiness. Besides, evaluating the RED using the proposed model will reveal the true characteristics of RED that are not apparent with simpler models, thus providing deeper insights into congestion control mechanisms.

The structure of this paper is organized as follows: Section 2 presents a comprehensive review of the literature on AQM and traffic modeling techniques. Section 3 details the proposed approach, including developing the RED model and the traffic modeling process. Section 4 discusses the outcomes of the MMBP-SD model and evaluates RED's performance using this model. Finally, the conclusions and future work are outlined in Section 5.

2. Literature review

Queue modeling techniques, such as Renewal Traffic and Bernoulli Processes, have been widely used to evaluate and validate the performance of congestion control algorithms in networking and traffic management [5]. These models offer a mathematical framework to represent traffic patterns and provide insights into system behavior under various conditions. However, these traditional models often fail to capture real-world traffic's discrete, bursty, and correlated characteristics. To overcome these limitations, the MMBP is utilized. The MMBP effectively captures network traffic's discrete, bursty, and correlated nature, making it a valuable tool in congestion control analysis and optimization.

MMBP's ability to represent variable traffic states and transitions between these states aligns well with the needs of congestion control evaluations. For instance, Alsaaidah, et al. [8] implemented the BLUE method with two-state and four-state MMBP models to prove that MMBP best suits the congestion control evaluation. Despite these findings, the question of whether the BLUE method performs optimally under MMBP conditions remains unproven, given the disparity in arrival rates between BP and MMBP models. This indicates a need for further comparative analysis to determine the efficacy of congestion control algorithms under different traffic modeling scenarios.

Duran, et al. [9] presented a novel discrete dynamical model of RED employing a beta distribution to manage bifurcations and chaos in internet congestion control. This model incorporates the unique characteristics of chaotic networks, proposing a generalized RED-based framework with two additional control parameters for the nonlinear packet drop probability function. In another study, Li, et al. [10] introduced a congestion control technique for Wireless Sensor Networks (WSNs) that utilizes a dual-threshold cache state in the router buffer to mitigate congestion. This method extends the RED algorithm by adjusting packet dropping based on a degree threshold. However, as the number of connections increases, the RED algorithm's reliance on average queue length often leads to increased transmission delays and unstable network performance. Although these approaches address the chaotic behavior of internet traffic, they do not incorporate the MMBP in their simulations.

Sunitha, et al. [11] explored the effectiveness of using a two-state MMBP for RED evaluation and analysis. Through the experiments, the MMBP was found to improve the fairness and stability of the network, as well as reduce packet loss and delay. Smiesko, et al. [12] focused on advancing traffic modeling with MMBP, assessing its performance in congestion control scenarios. Their findings indicated that the MMBP-based model offers a more precise depiction of bursty and correlated traffic patterns, thereby improving congestion management in router buffers.

Mahawish and Hassan [6] evaluated the RED algorithm's performance using a four-state MMBP. Their findings indicated that MMBP effectively captures traffic burstiness and correlation, enhancing congestion control in router buffers. Guan, et al. [13] conducted network simulations to implement RED with a two-state MMBP with a state of highly generated traffic and another for variable traffic volume with probability in the range from 0 to 1. The results were used to set the optimal value for the thresholds used in RED. In another study, Guan, et al. [14] proposed an AQM method tested and optimized using the MMBP-2 framework. Two states of low-generated traffic were used with probabilities in the range of 0.20 to 0.25. Guan, et al. [15] introduced an alternative AQM method to manage congestion and delay within router buffers, simulating traffic using a two-state MMBP with arrival probabilities between 0.20 and 0.25. Lim, et al. [16] developed an AQM approach to handle multiple aggregated and correlated traffic flows. They created a simulation environment featuring N overlapping flows, modeled with two-states MMBP under various settings to replicate moderate and heavy traffic conditions.

Saaidah, et al. [17] optimized the performance of the BLUE method using two-state MMBP, which resulted in optimized parameters and improved overall performance. Besides, Alsaaidah, et al. [8]

compared the performance of the BLUE and Gentle BLUE methods using two-state MMBP. Their findings corroborated those obtained with the Bernoulli Process (BP), demonstrating that Gentle BLUE outperforms the BLUE method. Abu-Shareha, et al. [5] assessed the RED method's performance under different traffic models, including BP, MMBP-2, and MMBP-4. Their results indicated that MMBP-4 provides superior traffic modulation, accurately reflecting the RED method's performance across multiple evaluation metrics during heavy congestion. This highlights the potential of MMBP-4 as an effective tool for evaluating and enhancing congestion control mechanisms. Accordingly, three different approaches are used to simulate traffic in: BP, MMBP-2, and MMBP-4, which will be used for comparison. Table 1 summarizes the discussed literature.

Table 1. Summary of the related work

Ref.	Method	BP	MMBP-2	MMBP-4	SD
Alsaaidah, et al. [8]	BLUE	√	√	√	χ
Duran, et al. [9]	RED	√	χ	χ	χ
Li, et al. [10]	Ext.RED	√	χ	χ	χ
Sunitha, et al. [11]	RED	√	√	χ	χ
Smiesko, et al. [12]	RED	√	√	χ	χ
Mahawish and Hassan [6]	RED	√	√	√	χ
Guan, et al. [13]	RED	√	√	χ	χ
Guan, et al. [14]	Proposed AQM	√	√	χ	χ
Guan, et al. [15]	Proposed AQM	√	√	χ	χ
Lim, et al. [16]	Proposed AQM	√	√	χ	χ
Saaidah, et al. [17]	BLUE	√	√	χ	χ
Abu-Shareha, et al. [5]	RED	√	√	√	χ
Proposed	RED	√	√	√	√

3. The Proposed work

The proposed framework leverages the stationary distribution of MMBP to simulate bursty traffic patterns for evaluating and benchmarking the RED algorithm. By providing deeper insights into RED's performance across various network conditions, this approach contributes to the ongoing refinement of congestion control strategies in modern computer networks. Utilizing MMBP offers flexibility in modeling traffic burstiness through multiple states. While MMBP is typically configured with two states (congested and non-congested), employing four states allows for finer granularity in congestion control. Moreover, the stationary distribution ensures precise traffic load settings, enhancing the accuracy of performance evaluations.

In modeling the network traffic, the packet arrival in slot k is modeled as a binomial distribution, with a probability α for a successful packet arrival. The time gap between two consecutive arrivals follows a geometric distribution. The arrival process remains in the same state with a probability of p and is transmitted into other states with collective probabilities equal to the complementary of p (i.e., $1-p$). During these processes, RED is implemented to decide on the accommodation of the packets. The performance evaluation is conducted after running through all the slots as determined.

In network traffic modeling, packet arrival in slot k is represented by a binomial distribution, α denoting the probability of a successful packet arrival. The time interval between consecutive arrivals follows a geometric distribution. The arrival process remains in the same state with a probability p and transitions to other states with collective probabilities summing to 1-p. Throughout these processes, the RED algorithm is applied to decide on the accommodation of packets. Performance evaluation is conducted after processing all the predetermined slots. Fig. 2 illustrates the proposed framework for comparing the performance of RED using the designed MMBP-SD model.

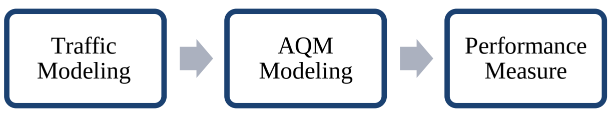


Figure. 2 MMBP-based Framework

3.1 Traffic modeling

Using the MMBP, the occurrence of packet arrivals depends on the probability associated with the model's current state. Specifically, the proposed MMBP model employs four distinct states (s_1, s_2, s_3, s_4), each characterized by unique packet arrival probabilities (α_1, α_2, α_3, α_4), and transition probabilities of ({p_{11}, p_{12}, p_{12}, p_{14}}, { p_{21}, p_{22}, p_{23}, p_{24}}, {p_{31}, p_{32}, p_{33}, p_{34}}, {p_{41}, p_{42}, p_{43}, p_{44}}). The model begins in the initial state, s_1. The packet arrival in the first slot depends on the probability α_1 associated with this state. In subsequent time slots, packet arrivals depend on either the probability of remaining in the current state or transitioning to a different state, as determined by the transition probabilities. These dynamics are governed by Eqs. (1) to (4).

$$P_{s_1} = \alpha_1 * p_{11} + (p_{21} * \alpha_2) + (p_{31} * \alpha_3) + (p_{41} * \alpha_4) \tag{1}$$

$$P_{s_2} = \alpha_1 * p_{12} + (p_{22} * \alpha_2) + (p_{32} * \alpha_3) + (p_{42} * \alpha_4) \tag{2}$$

$$P_{s_3} = \alpha_1 * p_{13} + (p_{23} * \alpha_2) + (p_{33} * \alpha_3) + (p_{43} * \alpha_4) \tag{3}$$

$$P_{s_4} = \alpha_1 * p_{14} + (p_{24} * \alpha_2) + (p_{34} * \alpha_3) + (p_{44} * \alpha_4) \tag{4}$$

The proposed MMBP model is characterized by α, α_s, and P_s, where α represents the overall target traffic load, α_s denote the probabilities of traffic load at different states, and P_s signifies the transition probabilities between these states. The combination of α_s and P_s ensures that the overall traffic load $\boldsymbol{\alpha}$ is achieved while accurately representing traffic burstiness. This integration allows the model to simulate realistic traffic patterns, capturing both the average load and its variations.

First, the transmission probabilities of the model are established, combining random and predetermined values. These probabilities are defined by Eqs. (5) to (7).

$$p_{ii} = random \in (0 \; to \; 1) \tag{5}$$

$$p_{ij}, p_{ik} = random \in ((0 \; to \; (1 - p_{ii})/3)) \tag{6}$$

$$p_{il} = 1 - (p_{ii} + p_{ij} + p_{ik}) \tag{7}$$

where i represents a specific state; thus, p_{ii} represents the probability of remaining in the same state i. The parameters j, k, and l denote the transition probabilities to other states within the model, determined randomly. The transition probability p_{il} is calculated such that the sum of transition probabilities from each state equals 1.

The calculated transition probabilities form the transmission matrix represented in Eq. (8).

$$A = \begin{bmatrix} p_{11} & p_{12} & p_{13} & p_{14} \\ p_{21} & p_{22} & p_{23} & p_{24} \\ p_{31} & p_{32} & p_{33} & p_{34} \\ p_{41} & p_{42} & p_{43} & p_{44} \end{bmatrix} \tag{8}$$

In order to set α_s, the constructed model uses the *stationary distribution* of the Markov chain. The stationary distribution refers to the long-term behavior of a stochastic process, indicating where it tends to settle over time. The stationary distribution is computed based on the transition matrix, A. The transpose of the matrix is calculated, and then the eigenvalues and eigenvectors of the transpose are calculated—next, the eigenvector corresponding to the eigenvalue one is selected and normalized to obtain the stationary distribution.

For a Markov chain, the stationary distribution is represented by a vector v, calculated using the transition matrix A and satisfies Eq. (9).

$$Av = v \tag{9}$$

Solving Eq. (9) is eased through Eqs. (10) to (13).

$$v_1 = (v_1 * p_{11}) + (v_2 * p_{21}) + (v_3 * p_{31}) + (v_4 * p_{41}) \tag{10}$$

$$v_2 = (v_1 * p_{12}) + (v_2 * p_{22}) + (v_3 * p_{32}) + (v_4 * p_{42}) \tag{11}$$

$$v_3 = (v_1 * p_{13}) + (v_2 * p_{23}) + (v_3 * p_{33}) + (v_4 * p_{43}) \tag{12}$$

$$v_1 + v_2 + v_3 + v_4 = 1 \tag{13}$$

Finally, to achieve the overall probability α, the stationary distribution is used to calculate the probabilities for each state α_1, α_2, α_3, and α_4, as shown in Eq. (14).

$$[v_1 \; v_2 \; v_3 \; v_4] * \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \\ \alpha_4 \end{bmatrix} = \alpha \rightarrow \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_3 \\ \alpha_4 \end{bmatrix} = [v_1 \; v_2 \; v_3 \; v_4]^{-1} * \alpha \tag{14}$$

As such, the arrival probabilities at different states, (α_1, α_2, α_3, α_4) are calculated by multiplying the

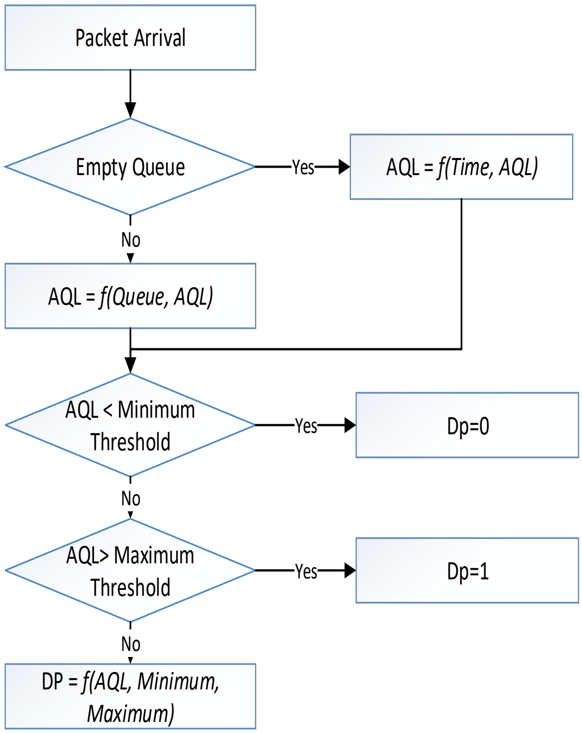


Figure. 3 RED Operations

inverse *v* vector with the overall probability α.

3.2 AQM modeling

RED is depicted in Fig. 3, operating through a series of defined procedures. Primarily, it determines packet-dropping probability (Dp) by comparing it with two thresholds. The Average Queue Length (AQL) is computed using Eq. (15) when the queue is empty and Eq. (16) when it's not.

$$AQL_t = (1 - w)^{idle} * AQL_{t-1} \quad (15)$$

$$AQL_t = (1 - w) * AQL_{t-1} + w * q_t \quad (16)$$

where w is the queue weight, which is determined empirically or initialized by experts, and idle is the time of idleness of the queue.

AQL is a critical metric for assessing queue congestion levels, guiding the calculation of Dp and the extent of packet-dropping measures. The comparison of AQL with the Minimum and Maximum Thresholds determines the course of action: if AQL falls below the minimum, Dp is set to 0, indicating no packet drops. In cases where AQL lies between the two thresholds, Dp is computed as a function of AQL's position relative to these thresholds. Lastly, if AQL surpasses the maximum threshold, signaling severe congestion, *Dp* is set to 1, dropping all incoming packets.

The implementation of RED employs an IF-Then approach, leveraging pre-initialized thresholds, max parameters, and counters set to specific and consistent values.

3.3 Performance measures

The delay (D), the dropping rate (DR), and the packet loss rate (PL) are used to evaluate the compared AQM methods. The *D* is calculated using Little's law, as given in Eq. (17), while DR and PL are represented in Eqs. (18) and (19), respectively.

$$D = MQL/T \quad (17)$$

$$DR = Dropped/Arrived \quad (18)$$

$$PL = Lost/Arrived \quad (19)$$

where *N* is the router capacity, *i* is a value between [0, N], indicating specific queue length, and p_i is the probability (i.e., the occurrences) of each length during the simulation. T is the throughput. PL is the ratio of lost packets to the number of packets that arrive at the router, while DR is the ratio of the dropped packets.

To evaluate the burstiness factor of the proposed approach, two burstiness factors are utilized; these are the Burstiness Factor (BF) and the Maximum Burstiness Duration (MBD), as given in Eqs. (20) and (21).

$$BF = \sigma_{interArrival}/\mu_{interArrival} \quad (20)$$

$$MBD = maximum\_length(cons.Arrival) \quad (21)$$

where $\sigma_{interArrival}$ is the standard deviation of the inter-arrival times between each pair of consecutive packets, while $\mu_{interArrival}$ is the mean of the inter-arrival times. MBD is the maximum length of the burst packets.

4. Simulation and results

The simulation components are illustrated in Fig. 4. RED and the network are simulated using the Java programming language. The network setup consists of a single router with a defined buffer capacity, where the underlying AQM method is executed. Performance evaluation is conducted through experiments utilizing a discrete-time queue model.

Received: May 22, 2024. Revised: June 13, 2024.

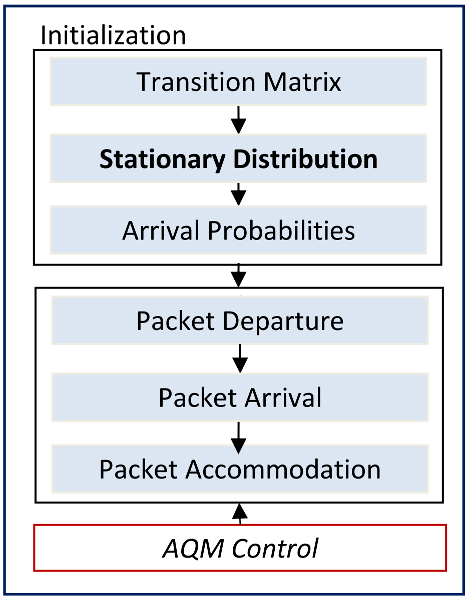


Figure. 4 Implementation details

Table 2. Parameter Settings

Parameter	Values
Overall Arrival Rate (α)	0.18-0.93
Departure Rates (β)	0.5, 0.3
Capacity	20
w	0.002
max-parameter	0.1
Minimum Threshold	3
Maximum Threshold	9

4.1 Parameter initialization

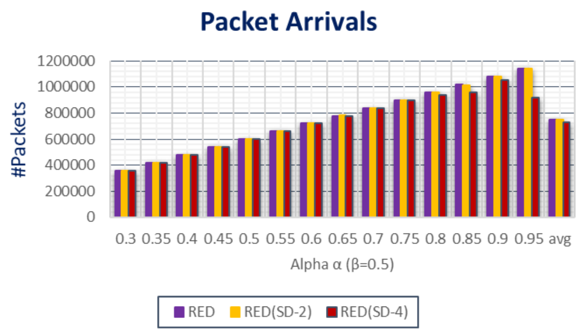
To evaluate RED effectively, it's essential to initialize specific parameters to predetermined values. These parameters include the arrival rate, departure rate, and capacity, which are pertinent to the simulated network. Additionally, parameters such as w, max-parameter, and the two thresholds are crucial for RED. It's worth noting that a series of experiments are conducted using various arrival and departure rates to simulate loads akin to congested and non-congested networks. Table 2 provides an overview of the parameters utilized in the experiments and their corresponding values.

4.2 MMBP-SD concepts validation

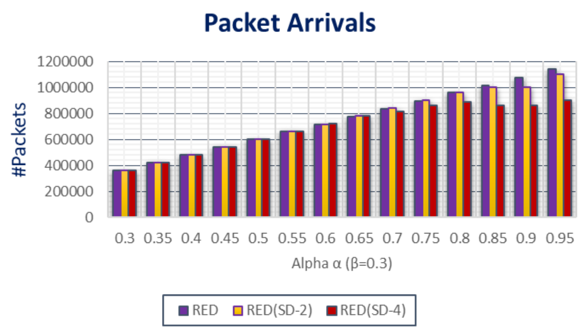
The arrival rates for each state in the different models can be found in Table 3. For a comprehensive understanding, the complete set of parameters, including transition and v values, are provided in Appendices A and B, respectively. It's important to note that all models exhibit variation in rates across different states, contributing to generating burst traffic using MMBP-SD-2 and MMBP-SD-4. Furthermore, to demonstrate the

Table 3. Arrival Rates of the Generated Models

α	BP	MMBPSD-2		MMBPSD-4			
	α_1	α_1	α_2	α_1	α_2	α_3	α_4
0.3	0.3	0.0408	0.3319	0.1398	0.0944	0.1503	0.4446
0.35	0.35	0.4225	0.1716	0.3528	0.0006	0.0010	0.0012
0.4	0.4	0.3340	0.4491	0.0965	0.0865	0.1880	0.5691
0.45	0.45	0.5056	0.3750	0.4257	0.0604	0.5308	0.4290
0.5	0.5	0.4223	0.5587	0.1534	0.7300	0.1689	0.1891
0.55	0.55	0.4818	0.6044	0.3297	0.8210	0.2473	0.2494
0.6	0.6	0.4131	0.7089	0.3261	0.8234	0.5160	0.4968
0.65	0.65	0.3206	0.7846	0.2223	0.9327	0.5149	0.2442
0.7	0.7	0.1807	0.8151	0.2272	0.1413	1.0000	0.2730
0.75	0.75	0.0539	0.7971	0.0190	0.8019	0.0204	0.0176
0.8	0.8	0.0308	0.8286	0.4837	0.6357	0.8876	0.9829
0.85	0.85	0.4644	1.0000	0.7010	0.7650	0.8162	1.0000
0.9	0.9	0.1652	1.0000	0.0507	1.0000	0.1615	0.2497
0.95	0.95	0.6573	1.0000	1.0000	0.3850	0.6282	0.7281



(a)



(b)

Figure. 5 Number of Packets Generated and Arrived by the Compared Models: (a) Arrival at β=0.5 and (b) Arrival at β=0.3

Table 4. Results of the burstiness evaluation

α	BP		MMBP-SD-4		MMBP-SD-4	
	BF	MBD	BF	MBD	BF	MBD
0.3	190.8	9	190.9	12	191.0	13
0.35	195.8	10	196.0	15	195.9	15
0.4	197.9	10	197.9	13	197.1	21
0.45	197.1	11	197.1	18	197.1	25
0.5	193.8	15	193.7	18	194.3	18
0.55	187.6	18	187.3	21	187.4	23
0.6	179	22	179.0	27	178.3	46
0.65	167.3	25	167.0	46	166.8	36
0.7	152.9	33	152.8	41	152.9	39
0.75	135.6	40	135.3	40	136.5	63
0.8	115.3	53	115.1	72	136.4	141
0.85	92.1	79	97.6	67	112.8	213
0.9	65.4	122	82.7	106	108.7	663
0.95	34.7	195	65.5	151	82.1	85
Average	150.4	45.9	154.1	46.2	159.8	100.1
Improve.	-	-	2.5%	1%	6.2%	118%

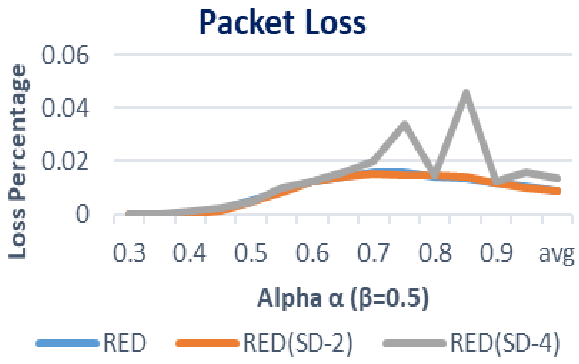
efficacy of the developed model in achieving an overall packet arrival rate, the number of arrival packets at different α values was evaluated, as depicted in Fig. 5. It's worth noting that while the arrival rates of the models may appear similar, attaining identical values is inherently impossible, even with the re-implementation of the same model due to the stochastic nature of the packet-generating process. These results underscore the importance of a fair comparison between the evaluated models (i.e., BP and MMBP-SD).

The results, as given in Table 4, illustrate that the MMBP-SD generates more realistic and burstiness traffic, which outperformed BP under all the arrival rates. The results showed that the MMBP-SD generates an improvement of BF by 6.5% and MBD by 118%. As such, based on the results for burstiness and arrival stability, the proposed approach achieved the desired property of modeling the burstiness of the traffic and allowed the overall arrival rate to be set concisely.

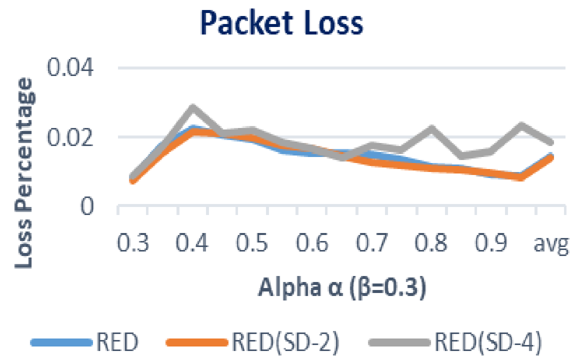
4.3 Experimental results

The experimental results assess the performance of RED using BP, MMBPSD-2, and MMBP-SD-4 across various arrival and departure probabilities.

Fig. 6 presents the evaluation results in terms of packet loss, depicting different load conditions ranging from low to high traffic, covering scenarios from non-congestion to heavy congestion. The departure rate (β) remains consistent at values of 0.5 and 0.3.



(a)

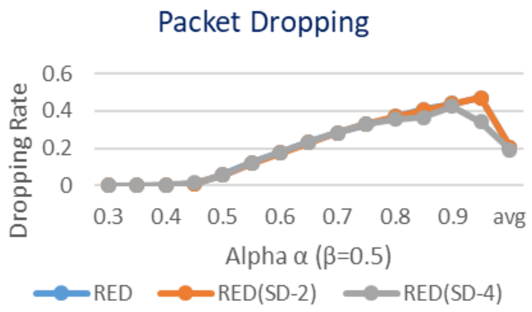


(b)

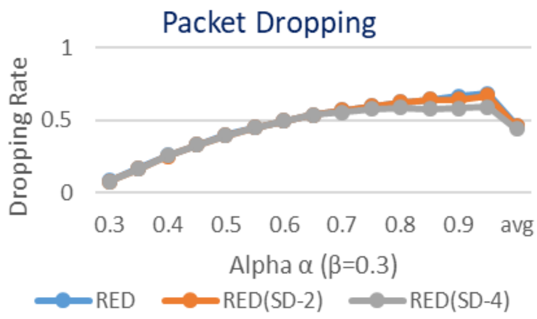
Figure. 6 Packet Loss-based Performance Comparison: (a) Loss at β=0.5 and (b) Loss at β=0.3

Notably, RED exhibits an average packet loss of 0.8% with β equal to 0.5 and 1.4% with β equal to 0.3. However, these percentages significantly deviate in the MMBP-SD-4 model, where packet loss reaches 1.3% and 1.8% for β, equal to 0.5 and 0.3, respectively. On average, RED loses 28.5% more using MMBP-SD-4.The disparities in packet loss become more pronounced in highly congested networks. Consequently, it is suggested that evaluating RED using single or double states may not fully capture its characteristics. Additionally, the performance gap becomes evident as the arrival rate surpasses certain thresholds [α= 0.65, β= 0.5] and [α= 0.4, β= 0.3].

Fig. 7 displays the evaluation outcomes regarding packet dropping. It is observed that, on average, RED drops 20% of the packets with β equal to 0.5 and 47% with β equal to 0.3, indicating its limited ability to respond to sudden fluctuations in network traffic load. Furthermore, the performance of BP and MMBP-SD-

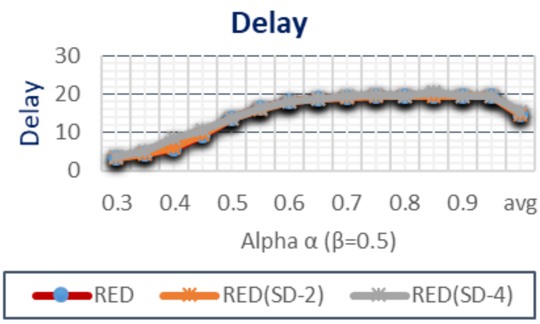


(a)

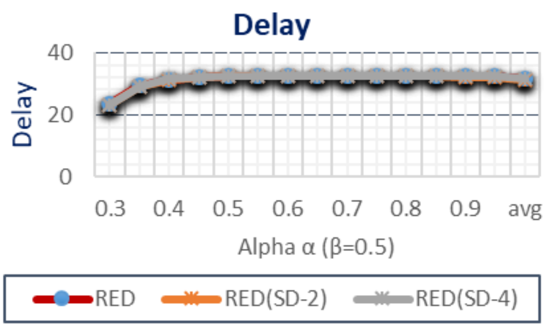


(b)

Figure. 7 Packet Dropping-based Performance Comparison: (a) Dropping at β=0.5 and (b) Loss at β=0.3



(a)



(b)

Figure 8. Delay-based Performance Comparison: (a) Delay at β=0.5 and (b) Delay at β=0.3

2 exhibits nearly identical behavior, implying that employing MMBP-SD-4 provides deeper insights into the AQM characteristics compared to the other models.

In Fig. 8, the evaluation results based on delay are depicted. It is noteworthy that the delay values are consistent across both models. Consequently, it can be concluded that while the dropping and delay behaviors are similar, packet loss stems from the sudden congestion generated in the MMBP-SD model, indicating RED's inadequate handling of such scenarios.

5. Conclusion

This study leverages the stationary distribution property of Markov chains to emulate the traffic load in network simulations. The results showed that the MMBP-SD generates an improvement of BF by 6.2% and MBD by 118% compared to BP. Besides, the results showed that using MMBP-SD-4 outperformed MMBP-SD-2 under all the arrival rates. Besides, the results of using MMBP-SD-4 indicate that RED's packet loss increases by 28.5% under the 4-state MMBP-SD model compared to the BP model, highlighting RED's limitations in handling burst traffic. Our findings illuminate distinct characteristics of RED when confronted with a 4-state Markov chain compared to single and 2-state models. Specifically, the results indicate increased packet loss in the 4-state model while the dropping behavior remains consistent. This disparity underscores RED's limitations in effectively managing burstiness and fluctuations in traffic load, nuances that are often overlooked in Bernoulli or 2-state models. Expanding on these insights, it becomes evident that traditional traffic modeling approaches fail to capture the intricacies of real-world network behavior, particularly when faced with dynamic and unpredictable traffic patterns. The adoption of the MMBP, especially in multi-state configurations, offers a more nuanced representation of traffic dynamics, allowing for a more accurate evaluation of congestion control mechanisms like RED.

Notation list

Symbol	Description
α	Overall Arrival Rate
β	Departure Rate
w	Queue Weight
max	Maximum Parameter for RED Algorithm
AQL	Average Queue Length
Dp	Packet Dropping Probability

q_t	Queue Length at Time t
q_{t-1}	Queue Length at Previous Time t−1
idle	Time of Idleness of the Queue
v	Stationary Distribution Vector
p_{ij}	Transition Probability from State i to j
v_1,v_2,v_3,v_4	Stationary Distribution Components
$\alpha_1,\alpha_2,\alpha_3,\alpha_4$	Arrival Probabilities in Different States
BF	Burstiness Factor
MBD	Maximum Burstiness Duration

Conflicts of Interest

The authors declare no conflict of interest.

Author Contributions

Conceptualization, Ahmad Adel Abu-Shareha; methodology, Mohammad A. Alsharaiah; software, Mosleh M. Abualhaj; validation, Adeeb Al-Saaidah; formal analysis, Qusai Shambour; resources, Ahmad Adel Abu-Shareha; writing—original draft preparation, Ahmad Adel Abu-Shareha; writing—review and editing, Qusai Shambour; supervision, Ahmad Adel Abu-Shareha; funding acquisition, Ahmad Adel Abu-Shareha".

Acknowledgments

This work was supported by Al-Ahliyya Amman University–Jordan.

References

[1] A. A. A. Shareha, A. Alsaaidah, A. Alshahrani, and B. Al-Kasasbeh, "Fuzzy-Based Active Queue Management Using Precise Fuzzy Modeling and Genetic Algorithm", *Symmetry*, Vol. 15, No. 9, p. 1733, 2023.

[2] G. Abbas, Z. Halim, and Z. H. Abbas, "Fairness-driven queue management: A survey and taxonomy", *IEEE Communications Surveys & Tutorials*, Vol. 18, No. 1, pp. 324-367, 2015.

[3] S. T. A. Jafri, I. Ahmed, S. Ali, and F. Qamar, "Analysis of AgRED Performance in LR-WPAN Dense Ad-Hoc Networks", *Engineering Proceedings*, Vol. 32, No. 1, p. 5, 2023.

[4] K. A. Nassar and A. A. Abdullah, "Fuzzy RED to Reduce Packet Loss in Computer network", *Journal of AL-Qadisiyah for Computer Science and Mathematics*, Vol. 8, No. 1, pp. 107-114, 2016.

[5] A. A. Shareha, M. Abualhaj, A. Alshahrani, and B. Al-Kasasbeh, "A four-state Markov model for modelling bursty traffic and benchmarking of random early detection", *International Journal of Data and Network Science*, Vol. 8, No. 2, pp. 1151-1160, 2024.

[6] A. A. Mahawish and H. J. Hassan, "Improving RED algorithm congestion control by using the Markov decision process", *Scientific Reports*, Vol. 12, No. 1, p. 13363, 2022.

[7] I. Zaryadov, A. Korolkova, D. Kulyabov, T. Milovanova, and V. Tsurlukov, "The survey on Markov-modulated arrival processes and their application to the analysis of active queue management algorithms", In: *Proc. of the Distributed Computer and Communication Networks: 20th International Conf, Moscow*, Russia, pp. 25–29 , 2017.

[8] A. Alsaaidah, M. Zalisham, M. Fadzli, and H. Abdel-Jaber, "Markov-modulated bernoulli-based performance analysis for gentle blue and blue algorithms under bursty and correlated traffic", *Journal of Computer Science*, 2016.

[9] G. Duran, J. Valero, J. M. Amigó, Á. Giménez, and O. Martinez-Bonastre, "Bifurcation analysis for the Internet congestion", In: *Proc. of the IEEE Conference on Computer Communications Workshops (INFOCOM 2019)*, Paris, France, 29 April- 2 May, 2019.

[10] S. Li, Q. Xu, J. Gaber, Z. Dou, and J. Chen, "Congestion control mechanism based on dual threshold DI-RED for WSNs", *Wireless Personal Communications*, Vol. 115, pp. 2171-2195, 2020.

[11] G. Sunitha, S. D. Kumar, and B. V. Kumar, "A pre-emptive multiple queue based congestion control for different traffic classes in WSN", In: *Proc. of the International Conf on Circuits, Communication, Control and Computing*, Bangalore, India, pp. 21-22, 2014.

[12] J. Smiesko, M. Kontsek, and K. Bachrata, "Markov-Modulated On–Off Processes in IP Traffic Modeling", *Mathematics*, Vol. 11, No. 14, p. 3089, 2023.

[13] L. Guan, I.-U. Awan, and M. E. Woodward, "Stochastic modelling of random early detection based congestion control mechanism for bursty and correlated traffic", *IEE Proceedings-Software*, Vol. 151, No. 5, pp. 240-247, 2004.

[14] L. Guan, M. E. Woodward, and I. U. Awan, "Stochastic modelling of maintaining specified QoS constraints in discrete-time domain", In: *Proc. of the 13th International Conf on Computer Communications and Networks*, Chicago, IL, USA, 11-13 October, 2004.

[15] L. Guan, M. E. Woodward, and I. U. Awan, "Bounding delay through a buffer using dynamic queue thresholds", In: *Proc. of the 20th*

International Conf on Advanced Information Networking and Applications-Volume 1 (AINA'06), Vienna, Austria, pp. 18-20, 2006.

[16] L. B. Lim, L. Guan, A. Grigg, I. W. Phillips, X. G. Wang, and I. U. Awan, "Controlling mean queuing delay under multi-class bursty and correlated traffic", *Journal of Computer and System Sciences*, Vol. 77, No. 5, pp. 898-916, 2011.

[17] A. M. Saaidah, M. Z. Jali, M. F. Marhusin, and H. Abdel-jaber, "Markov-modulated Bernoulli-based performance analysis for BLUE algorithm under bursty and correlated traffics", In: *Proc. of the 2014 International Conf on Computer, Communications, and Control Technology (I4CT)*, Langkawi, Malaysia, pp. 2-4, 2014.

Appendix A. The Parameters of the MMBP-SD-2 Model

α	**Arrival Rate**		**v**		**Transition Matrix (A)**	
	α_1	**α_2**	**v_1**	**v_2**		
0.3	0.0408	0.3319	0.1094	0.8906	0.1753	0.8247
					0.1013	0.8987
0.35	0.4225	0.1716	0.7111	0.2889	0.9460	0.0540
					0.1330	0.8670
0.4	0.3340	0.4491	0.4265	0.5735	0.0307	0.9693
					0.7208	0.2792
0.45	0.5056	0.3750	0.5741	0.4259	0.6403	0.3597
					0.4850	0.5150
0.5	0.4223	0.5587	0.4305	0.5695	0.4207	0.5793
					0.4379	0.5621
0.55	0.4818	0.6044	0.4435	0.5565	0.4068	0.5932
					0.4728	0.5272
0.6	0.4131	0.7089	0.3682	0.6318	0.3401	0.6599
					0.3846	0.6154
0.65	0.3206	0.7846	0.2901	0.7099	0.8418	0.1582
					0.0646	0.9354
0.7	0.1807	0.8151	0.1814	0.8186	0.3357	0.6643
					0.1472	0.8528
0.75	0.0539	0.7971	0.0634	0.9366	0.3568	0.6432
					0.0435	0.9565
0.8	0.0308	0.8286	0.0358	0.9642	0.1296	0.8704
					0.0324	0.9676
0.85	0.4644	1.0000	0.3119	0.6881	0.3053	0.6947
					0.3149	0.6851
0.9	0.1652	1.0000	0.1395	0.8605	0.6637	0.3363
					0.0545	0.9455
0.95	0.6573	1.0000	0.3695	0.6305	0.6522	0.3478
					0.2038	0.7962

Appendix B. The Parameters of the MMBP-SD-4 Model

α	Arrival Rate				v				Transition Matrix (A)			
	α_1	α_2	α_3	α_4	v_1	v_2	v_3	v_4				
0.3	0.1398	0.0944	0.1503	0.4446	0.1686	0.1139	0.1813	0.5362	0.4161	0.1869	0.0696	0.3274
									0.5844	0.2737	0.0709	0.0710
									0.0387	0.1462	0.7360	0.0790
									0.0464	0.0461	0.0523	0.8552
0.35	0.3528	0.0006	0.0010	0.0012	0.9920	0.0018	0.0028	0.0034	0.9995	0.0001	0.0001	0.0003
									0.1648	0.7418	0.0686	0.0247
									0.0416	0.0965	0.8466	0.0153
									0.0141	0.0214	0.0710	0.8934
0.4	0.0965	0.0865	0.1880	0.5691	0.1026	0.0920	0.2000	0.6054	0.5880	0.0401	0.0271	0.3449
									0.3694	0.0004	0.3322	0.2980
									0.0183	0.4315	0.4823	0.0679
									0.0076	0.0027	0.1159	0.8738
0.45	0.4257	0.0604	0.5308	0.4290	0.2944	0.0418	0.3671	0.2967	0.8851	0.0024	0.0029	0.1095
									0.4890	0.3606	0.1389	0.0115
									0.0021	0.0688	0.9041	0.0249
									0.0425	0.0025	0.0962	0.8589
0.5	0.1534	0.7300	0.1689	0.1891	0.1236	0.5880	0.1360	0.1524	0.7055	0.0071	0.0591	0.2283
									0.0587	0.9048	0.0221	0.0144
									0.0093	0.3346	0.5959	0.0602
									0.0040	0.0627	0.2276	0.7057
0.55	0.3297	0.8210	0.2473	0.2494	0.2001	0.4984	0.1501	0.1514	0.4911	0.0499	0.0300	0.4290
									0.1617	0.7620	0.0525	0.0239
									0.0745	0.4798	0.2534	0.1923
									0.0666	0.2419	0.5278	0.1636
0.6	0.3261	0.8234	0.5160	0.4968	0.1508	0.3808	0.2386	0.2297	0.1946	0.0326	0.1353	0.6375
									0.1575	0.6642	0.0898	0.0884
									0.0987	0.4435	0.3601	0.0977
									0.1652	0.0745	0.4269	0.3334
0.65	0.2223	0.9327	0.5149	0.2442	0.1161	0.4873	0.2690	0.1276	0.3097	0.0242	0.1186	0.5475
									0.1038	0.8303	0.0114	0.0546
									0.0630	0.2752	0.5709	0.0909
									0.0991	0.0460	0.7533	0.1016
0.7	0.2272	0.1413	1.0000	0.2730	0.1382	0.0859	0.6098	0.1661	0.4570	0.0981	0.0279	0.4171
									0.5235	0.1653	0.1864	0.1247
									0.0135	0.0760	0.8898	0.0207
									0.1316	0.0711	0.2850	0.5123
0.75	0.0190	0.8019	0.0204	0.0176	0.0221	0.9336	0.0238	0.0205	0.0112	0.2541	0.0504	0.6844
									0.0145	0.9797	0.0049	0.0009
									0.3081	0.4948	0.0552	0.1419
									0.0484	0.0793	0.8167	0.0557
0.8	0.4837	0.6357	0.8876	0.9829	0.1618	0.2126	0.2969	0.3287	0.1452	0.1469	0.1075	0.6004
									0.5127	0.2513	0.0069	0.2291
									0.0036	0.4431	0.3565	0.1968
									0.0857	0.0118	0.5238	0.3787
0.85	0.7010	0.7650	0.8162	1.0000	0.2110	0.2303	0.2457	0.3130	0.2321	0.1631	0.2462	0.3586
									0.3744	0.4233	0.1608	0.0415

									0.2580	0.3823	0.2255	0.1342
									0.0398	0.0142	0.3238	0.6222
0.9	0.0507	1.0000	0.1615	0.2497	0.0309	0.7180	0.0986	0.1524	0.0842	0.0703	0.1409	0.7046
									0.0275	0.9571	0.0045	0.0109
									0.0452	0.2835	0.6680	0.0033
									0.0270	0.0043	0.1650	0.8037
0.95	1.0000	0.3850	0.6282	0.7281	0.4409	0.1236	0.2017	0.2338	0.8097	0.0571	0.0112	0.1220
									0.3794	0.3080	0.1178	0.1948
									0.1069	0.2024	0.6191	0.0716
									0.0661	0.0836	0.2453	0.6050