Analysis of a Random-Access Protocol Under Long-Range-Dependent Traffic

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***Abstract*—Aloha-type random-access protocols have been employed as access-control protocols in wireline and wireless, and stationary and mobile, multiple-access communications networks. They are frequently employed by the control and signaling subsystem of demand-assigned multiple-access protocols for regulating the sharing of a multiaccess communications channel. The correct design and sizing of the random-access operated control/signaling channel is a critical element in determining the performance of these networks. Excessive delays in the transport of signaling messages (induced by too many collisions and retransmissions) lead to unacceptable session-connection setup times. This is of particular concern when the message traffic is highly bursty, as it tends to be under a multitude of often-observed traffic-loading scenarios. Consequently, in this paper, we investigate the performance behavior of a random-access protocol when loaded by bursty traffic processes. The latter often exhibit long-range dependence (LRD). The LRD traffic flows are modeled here as multiplicative multifractal processes. The random-access protocol is modeled as an Aloha channel with blocking. We demonstrate that the burstiness feature of the traffic processes, rather than their LRD character, is the essential element determining the performance behavior of the protocol. When the loading-traffic process is not very bursty, we show that the performance of the random-access channel can be even better than that exhibited under Poisson traffic loading; otherwise, performance degradation is noted. We demonstrate the impact of the selection of the protocol-operational parameters in determining the effective performance behavior of the random-access protocol.**

***Index Terms*—Aloha, long-range dependence, multifractal traffic processes, multiple access, performance evaluation.**

I. INTRODUCTION

IN THE currently operating mobile, satellite, and other communications networks, Aloha-based random multiple-access schemes have been used extensively, especially for scenarios in which the activity factor of sources is low and low-packet delay is a primary requirement. Random-access schemes have also been used extensively for regulating access into control (or order-wire-type) channels for the transmission of reservation packets, as is the case for cellular wireless networks. It is essential to design such networks to yield acceptable packet-delay performance to ensure that users are allocated network resources in a timely manner to satisfy their required quality-of-service (QoS) performance level.

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Performance of Aloha schemes, especially the bistable behavior of the systems [1]–[4], has been under extensive study. The input-traffic process for an Aloha-based channel is typically modeled as a Poisson process [5]. Formulas have been developed to describe the channel's throughput and delay performance, which are used for network-dimensioning purposes. Recently, it has been observed that measured network-traffic data often exhibit long-range dependence (LRD). Such traffic processes include local-area-network (LAN) [6], wide-area-network (WAN) [7], variable-bit-rate (VBR) video [8], and world-wide-web (WWW) [9] traffic. Furthermore, it has been shown that the LRD property has a profound impact on the performance of a network. For example, Norros [10] has shown that the queue-length tail distribution under the fractional Brownian motion traffic model follows Weibull distribution in comparison with exponential distribution that is induced by a queuing system that is loaded by a Poisson or Markovian traffic-input process. Erramilli *et al.* [11] have shown that the mean delay time for a queuing system driven by some actual LAN traffic is much worse than that of a queuing system driven by certain traffic processes obtained by shuffling the order of packet arrivals of the measured traffic process in such a way that the marginal distribution of the constructed traffic is the same as that of the measured traffic, while the long-range correlations are lost. Gao and Rubin [12] have shown that a Poisson model often underestimates buffer-size or delay-time statistics by several orders of magnitude when compared to a queuing system driven by actual traffic trace data.

With LRD traffic measured in many data networks, one expects the aggregated traffic loading an Aloha-based channel to also possess such properties. Furthermore, one expects such LRD properties to have a significant impact on the performance of Aloha-based channels as well. This issue has been recently studied by Aracil and Munoz [13] and by Harpantidou and Paterakis [14]. By employing LRD real Telnet packet-arrival processes as input traffic, Aracil and Munoz have found that the Aloha channel actually performs much better than that loaded by a Poisson traffic. A similar result has been obtained by Harpantidou and Paterakis by employing a simple LRD traffic model with Pareto-distributed interarrival times as their input traffic. These results are quite the opposite of those presented by Norros [10], Erramilli *et al.* [11], and Gao and Rubin [12]. This situation and the ensuing importance of the model in many applications has motivated us to carefully study the performance of Aloha channels loaded by LRD traffic.

A key issue in traffic engineering in general and LRD traffic study in particular is the characterization of the burstiness of network traffic. An LRD traffic process is often characterized by the Hurst parameter $1/2 < H < 1$ [6], [8]. H characterizes the persistence of correlations in a traffic process and is often interpreted as an effective indicator of the burstiness of traffic [6]. Recently, we have found that although an LRD traffic process is sometimes very bursty, a burstier LRD traffic is not necessarily associated with a larger value for the Hurst parameter [15]. We show here that what really matters for the performance of an Aloha channel is not the LRD nature but the burstiness level of the traffic process. For this purpose, we employ a multiplicative multifractal traffic process [12], [15]–[22] as an LRD traffic model, since multiplicative multifractal traffic processes have very well-defined burstiness indicators. In this paper, we show that when the LRD traffic is not very bursty, the performance of the random-access channel can be much better than that produced under Poisson traffic loading; otherwise, a distinct performance degradation takes place. In light of these results, we conclude that neither the LRD Telnet arrival processes used by Aracil and Munoz [13] nor the Pareto traffic processes used by Harpantidou and Paterakis [14] are very bursty. In fact, by re-examining the model used in the latter paper, we have found that in constructing the Pareto traffic model, Harpantidou and Paterakis have selected the parameters for the Pareto traffic model in such a way that the modeled traffic becomes less and less bursty when the channel loading gets heavier.

The second purpose of this paper is to determine the desirable range for the selection of key parameter values for the random-access algorithm. This is performed to tune up the algorithm to operate effectively under multifractal traffic, under a wide range of burstiness level conditions.

The rest of the paper is organized as follows. In Section II, we describe the Aloha system adopted here and the multiplicative multifractal arrival traffic model. In Section III, we first study the performance of the Aloha system under Poisson traffic for purposes of comparing it with the same system loaded by multifractal traffic. We also examine the dependence of the performance of the system on different parameters. We then study the performance of the random-access scheme under multifractal traffic loading, assuming a wide range of burstiness levels. Finally, we draw conclusions in Section IV.

II. The Multiaccess Scheme and the Arrival Traffic Model

A. Slotted Aloha System With Blocking

The system studied here is the slotted Aloha multiple-access communications channel driven by a large (theoretically infinite) number of identical users. The aggregated traffic with mean arrival rate λ is modeled as a multiplicative multifractal process, which will be described shortly. Each terminal handles at most a single packet at a time. All transmitted packets have the same length. A packet transmission requires a single time slot. If only one user transmits a packet in a given time slot, the packet is assumed to be correctly received by the receiver. If two or more terminals transmit packets in the same time slot, a destructive collision occurs. For simplicity of the implementation of the system, we assume that what is detectable in a given time slot is whether the packets transmitted during the slot collide or not. The number of colliding packets is not assumed to be an observable given.

It is well known that the Aloha protocol is unstable (actually, it has been shown to be a bistable system with two equilibrium points [1]–[4], one desirable and the other undesirable), if not stabilized. There are two ways to stabilize the system. One is by employing blocking packets, the other without blocking [23], [24]. The latter scheme achieves this by incorporating an adaptive retransmission delay mechanism. In [23], it is shown that a stable operation results when the retransmission range of colliding packets is linearly adapted to the realized number of colliding packets in a previous time period. The latter variable cannot be practically observed, so an estimate for it must be employed. In [24, Section 4-2-3], considering Poisson arrival processes, it is similarly noted that a stable operation can be attained by adapting the retransmission probability of a colliding packet to the overall net backlog n, setting it to be of the order of $1/n$. Again, the net backlog cannot be directly observed by a station so that a recursive estimation procedure must be used. The latter requires the arrival rate parameter to be available or practically be estimated as well. Note, however, that these dynamically adaptable schemes require the use of estimation algorithms and during intense activity periods (resulting in large numbers of colliding packets and high backlog levels) many packets incur excessively long delays (since they will be retransmitted at a random time selected over a very long time period). This is generally not an acceptable mode of operation. In fact, we have observed in numerical simulations that when the system is operated under LRD traffic and the loading is not too low, the delay can be so long that the throughput of the system is very close to zero. Therefore, we shall not study this scheme in this paper.

The scheme employing blocking flow control is a more effective and better recognized method to stabilize the system. This is, thus, the operation that is assumed in this paper. Note that a blocking procedure is implemented in virtually all wireless networks (see, for example, the CDMA standard protocol for second-generation cellular wireless networks, whereby a maximum number of retransmission attempts is allowed, beyond which messages are blocked) and wireline LANs (see, for example, the Ethernet standard protocol, whereby a maximum number of retransmissions is imposed before a failure message is sent to the higher layer). Other networks employ a flow-control mechanism that blocks messages when the network becomes congested. (This is also part of the congestion and flow-control scheme used by TCP, which is employed by TCP/IP networks and across the Internet.)

To parallel many practical implementations (as noted above), where flow is controlled through the use of a blocking procedure, we design our system to work as follows (see the schematic of Fig. 1). A ready terminal transmits its packet at the start of a time slot. The system detects how many time slots experienced collisions during the most recent W time slots. If, at a given time slot, this number of collisions $N_{CS}(W)$ exceeds a threshold value T_H, then with probability P_b by considering independently all ready terminals, a ready terminal is blocked during this time slot. A blocked terminal discards its packet. Nonblocked ready terminals are permitted to transmit their

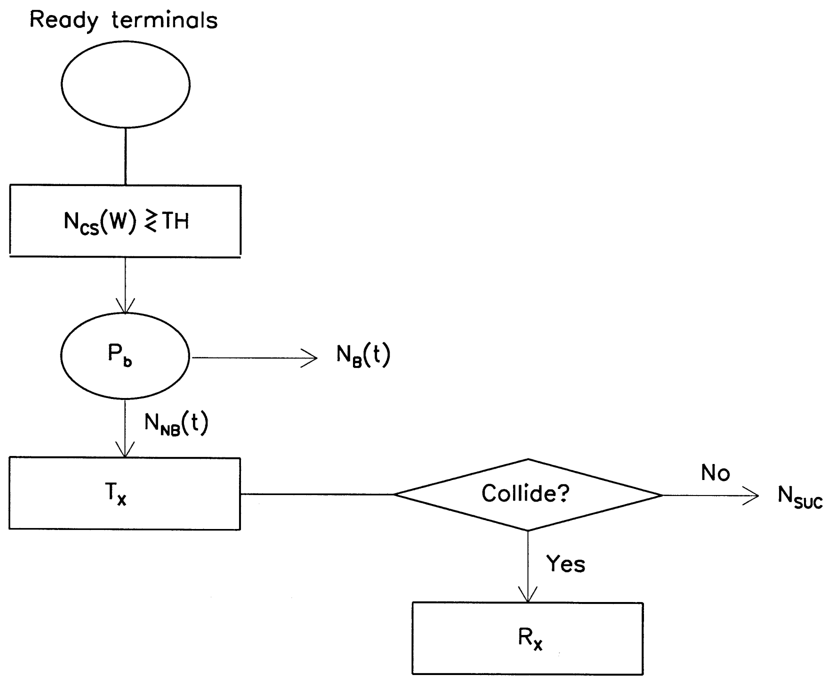

Fig. 1. Schematic of the random-access scheme.

packets at this time slot. Each nonblocked terminal checks to confirm whether its packet transmission resulted in a collision. If no collision is incurred, the transmission is declared successful. The collided packets are scheduled for retransmission at a later slot that is selected by using a uniform redistribution over a subsequent window of length L (slots).

Next, we describe the traffic model for the packet arrival process.

B. The Multiplicative Multifractal Arrival Traffic Model

We consider the interarrival times for the aggregate traffic representing the overall arrivals of packets to the system. Note that under a Poisson traffic model, the interarrival times are assumed to be exponentially distributed. Here we employ a multiplicative multifractal traffic model, as developed by us [12], [15]–[22]. The model is described as follows.

Construction Rule: Consider a unit interval. Associate it with a unit mass. Divide the unit interval into two (say, left and right) segments of equal length. Also, partition the mass into two fractions, r and $1-r$, and assign them to the left and right segments, respectively. The parameter r is in general a random variable, governed by a probability density function $P(r)$, $0 \leq r \leq 1$, which is symmetric about $r = 1/2$. The fraction r is called the multiplier and $P(r)$ is called the multiplier function. $P(r)$ is symmetric about $r = 1/2$ and has successive moments $\mu_1(= 1/2)$, $\mu_2, \ldots$. Each new subinterval and its associated weight (or mass) are further divided into two parts following the same rule. This procedure is schematically shown in Fig. 2, where the multiplier r is written as r_{ij}, with i indicating the stage number and j taking only odd integers indicating the position of the weight at that stage (leaving positions marked by even integers to $1 - r_{ij}$). Note that the scale (i.e., the interval length) associated with stage i is 2^{-i}. The weights at stage N, $\{w_n, n = 1, \ldots, 2^N\}$ can then be expressed as $w_n = u_1 u_2 \cdots u_N$, where u_l, $l = 1, \ldots, N$ are either r_{ij} or $1 - r_{ij}$. Thus, $\{u_i, i \geq 1\}$ are independent identically distributed random variables having pdf $P(r)$. The weights $\{w_n\}$ are employed to model the interarrival time series of the aggregate traffic process.

Among the interesting properties of multiplicative multifractal processes, we note the following [15], [19].

- $M_q(\epsilon) = E\left(\sum_{n=1}^{2^N} \left(w_n(N)\right)^q\right) \sim \epsilon^{\tau(q)}$ where $w_n(N)$ is a weight at stage N, q is (any) real number, $\epsilon = 2^{-N}$, $\tau(q) = -\ln(2\mu_q)/\ln 2$, and μ_q is the qth moment of the multiplier pdf $P(r)$.

  Mathematically, a fractal is characterized by a single power-law relation, while multifractals are characterized by many (possibly infinitely many) power-law relations. The above property, thus, states that multiplicative processes are multifractals.
- The weights at stage $N \gg 1$ have a log-normal distribution. We note that among the four different types of distributions—normal, lognormal, exponential, and Weibull—the lognormal distribution has been observed to most closely characterize certain features of WWW traffic, such as page size, page request frequency, and user's think time [25].
- Ideal multiplicative multifractals exhibit the LRD property, with the Hurst parameter given by $1/2 < H \leq -(1/2)\log_2 \mu_2 < 1$.

Since $P(r)$ is symmetric about $r = 1/2$, the mean value for the weights at stage N is 2^{-N}. In order to obtain an aggregated traffic with arrival rate λ, we simply choose the length of the time slot to be $2^{-N}\lambda$.

For simplicity, we choose the multiplier distribution to be Gaussian as follows:

$$P(r) \sim e^{-\alpha(r-1/2)^2}. \tag{1}$$

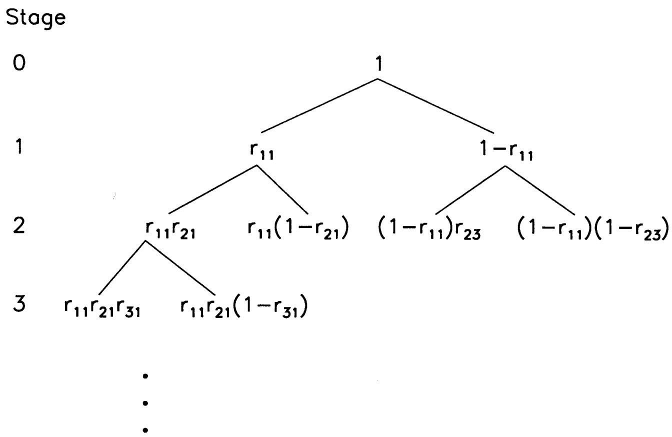

Fig. 2. Schematic of the construction rule.

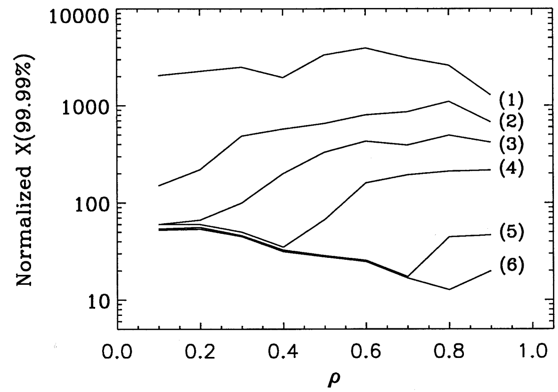

Fig. 3. Ratio of the 99.99th percentiles of the complimentary queue lengths for a FIFO queuing system driven by a multifractal traffic and that loaded with Poisson traffic. The six curves, denoted as (1) to (6) from top to bottom, correspond to $\alpha = 10$, 30, 50, 100, 400, and 1000.

The parameter α determines the burstiness of the traffic: the larger the value of α, the less bursty the traffic[16]. Typically, we generate a multifractal process by iterated computation that is carried out until we reach stage $N = 20$, so that the number of weights at our disposal is about one million.

Since the concept of the burstiness of the traffic plays a key role in this study, we first quantitatively determine how bursty a multifractal traffic process is (with given α). For this purpose, we consider a single-server first-in–first-out (FIFO) queueing system with an unlimited (infinite) capacity buffer. We drive the queuing system by a multiplicative multifractal traffic and compute the queue tail-size distribution. We choose the complimentary queue length corresponding to the 99.99th percentile tail value as our effective measure for the burstiness of the traffic. Such a procedure can, of course, also be carried out for such a queuing system loaded by a Poisson traffic process. We can then normalize the 99.99th percentile of the complimentary queue length for the multifractal traffic by that obtained under Poisson loading. We note several interesting features that are revealed by Fig. 3: 1) the multifractal traffic process is more bursty when α is smaller; 2) in terms of absolute burstiness, all the multifractal traffic processes studied here are much more bursty than the Poisson traffic; and 3) in terms of the rate of change of the burstiness, Poisson traffic can induce higher rates of such change when compared to not-very-bursty multifractal traffic processes. This phenomenon is elucidated by the downward-trending portion of curves (4)–(6) in Fig. 3. This feature might be reflecting that, for not-too-bursty multifractal traffic processes, the number of big bursts are quite few. As we shall show, after those big but few bursts are effectively blocked, the performance of the ALOHA system can be even better than that under Poisson traffic.

III. Performance of the Aloha System

In this section, we study the performance of the ALOHA channel under different parameter values. We employ five parameters: the burstiness parameter α, the window size W, the threshold value T_H for determining if blocking takes place, the blocking probability P_b, and the window size L for redistributing the transmissions of collided packets. For simplicity, we fix $L = 10$ for the illustrative cases presented in the following. To better understand the performance of the ALOHA system under multifractal traffic, we first exhibit the performance of the system under Poisson traffic.

A. Performance of the System Under Poisson Traffic

Assuming the arrival process of new packets to the random-access channel to be a Poisson process, it has been observed that the superimposed channel process of packet transmissions (consisting of new arrivals and of colliding packets) is clearly not a Poisson process. Nevertheless, it has been shown (and extensively confirmed via simulations, see [23], [26]) that the delay-throughput performance curve attained under a Poisson assumption for the superimposed channel process matches closely that calculated (through simulations) when no such an assumption is made. As shown in [26], the simplified performance equation is highly robust, applicable to independent arrival processes even when no Poisson assumption is made for the superimposed process. Consequently, the simplified performance equation has been employed by system designers to engineer such schemes. For comparison purposes, we state the well-known throughput formula for the system under Poisson traffic

$$s = Ge^{-G} \tag{2}$$

where s is the normalized throughput (representing the average number of successful packet transmissions per slot) and G denotes the total channel-loading rate (representing the average number of total packet transmissions, including successful and colliding transmissions, per slot). Assuming a window size of $W = 20$, we have carried out simulation-based evaluations to determine an effective threshold level (T_H) by varying the latter over the range [5,15] and calculating the resulting delay and throughput performance. We have found the best threshold to be $T_H = 10$. Fig. 4 shows the throughput versus channel-loading (G) performance curves under three selected values for the blocking probabilities, $P_b = 0.1$, 0.25, and 0.5. The thin solid curve is generated by using (2). We observe that all three dash-dot curves lie below the thin solid curve, indicating that the throughput of the system under Poisson arrival traffic is actually slightly lower than that predicted by (2) under the selected set of parameters (noting also that L is limited to a range of 10

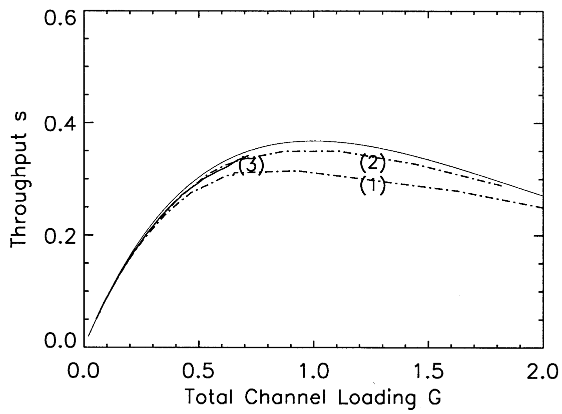

Fig. 4. Throughput s versus total channel loading G curves under Poisson traffic. The top-most solid thin line is generated from (2). The other three curves, denoted as (1), (2) (both dash-dot curves), and (3) (solid thick curve) correspond to $P_b = 0.1$, 0.25, and 0.5, respectively.

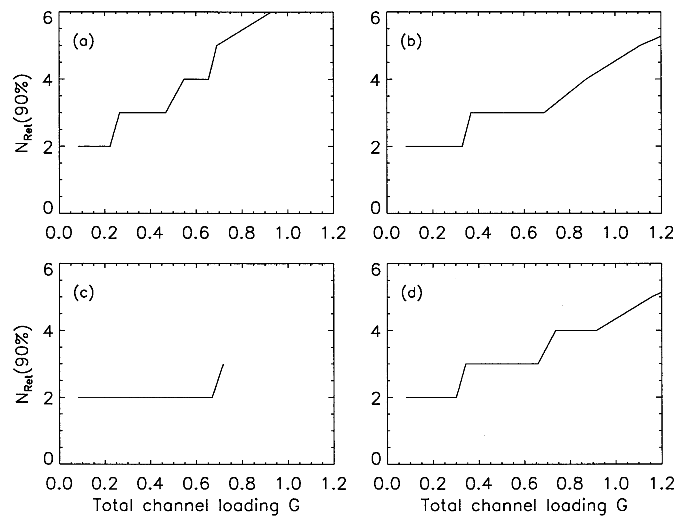

Fig. 5. The 90th percentile of the number of retransmissions versus the total channel loading G curves for Poisson traffic. (a) $P_b = 0.1$ and $(T_H, W) = (10, 20)$. (b) $P_b = 0.25$ and $(T_H, W) = (10, 20)$. (c) $P_b = 0.5$ and $(T_H, W) = (10, 20)$. (d) $P_b = 0.25$ and $(T_H, W) = (12, 20)$.

slots). We note that when P_b is small, such as 0.1, the throughput of the system [as represented by the curve (1) in Fig. 4] degrades, compared with the theoretical curve, as the loading rate increases. When P_b is increased to a level such as 0.25, the realized throughput level is distinctly improved, as shown by the curve (2) in Fig. 4. However, when P_b is further increased to a blocking level of 0.50, the maximum throughput level achieved is somewhat lower than that attained for $P_b = 0.25$, as indicated by the solid curve (3) in Fig. 4. In fact, curve (3) in Fig. 4 almost coincides with curve (2) for realizable loading G range. Under the parameters corresponding to curve (3), due to heavy blocking the loading G cannot be increased above around 0.7. As P_b is further increased, the attainable G range is shortened further and the maximum throughput level gradually continues to decrease.

Packet-delay time statistics also serve as important performance measures for an ALOHA system. Packet delay typically involves the calculation of delay only for packets that are successfully transmitted and not blocked. To assess the packet's delay performance, we examine the number of retransmissions incurred by a packet until it is successfully transmitted. Specifically, we compute the 90th percentile of the number of retransmissions, $N_{\rm Ret}$(90%). The $N_{\rm Ret}$(90%) statistic is a most-valuable measure of packet delay, since the delay statistics incurred by a packet that is (eventually) successfully transmitted is directly related to the number of retransmission statistic for successfully departing packets, noting that the delay is equal to the sum of the retransmission spans incurred during each retransmission attempt, plus the initial retransmission span. It is further noted that given the distribution of $N_{\rm Ret}$, the overall packet-delay duration statistics are directly calculated under the given retransmission delay scheme used. Furthermore, packet-delay moments and 90% levels are monotonically related to $N_{\rm Ret}$(90%).

In Fig. 5(a)–(c), we show the behavior of $N_{\rm Ret}$ (90%) versus the total channel loading G under Poisson traffic loading, for parameter values corresponding to the three curves exhibited in Fig. 4. It is interesting to note that the performance exhibited under $P_b = 0.1$ is worse than that observed for $P_b = 0.25$ in terms of both the realized throughput level [Fig. 4 curves (1) and (2)] and the attained delay performance as expressed by $N_{\rm Ret}$ (90%). For $P_b = 0.50$, however, an improved delay performance is observed, as expected, due to the high blocking level. Under the assumed conditions, we note that designs corresponding to parameters $P_b = 0.25$ and $(T_H, W) = (10, 20)$ [Fig. 4 curve (2) and to Fig. 5(b)] and $P_b = 0.5$ and $(T_H, W) = (10, 20)$ [Fig. 4 curve (3) and Fig. 5(c)] yield good performance behavior.

Note from Fig. 5(d), in comparison with Fig. 5(b), that as the threshold level is increased from $T_H = 10$ to $T_H = 12$, the message-delay performance somewhat degrades. Similar throughput performance features have been noted by us for the two cases (not shown here).

B. Performance of the System Under Multifractal Traffic

First we fix $\alpha = 100$ and study the performance of the system under different parameter values for T_H, W, and P_b. Following the same procedure for the selection of T_H for the ALOHA system under Poisson traffic loading, we find by numerical simulations that a good selection of (T_H, W) for the system under multifractal traffic is (7, 20). It turns out that for not-too-high channel-loading conditions, this parameter combination also works very well for the other studied α parameter values. Since an ALOHA channel is designed to work for not-too-high loading conditions, we fix (T_H, W) to be (7, 20) in the rest of the paper.

Next, we study the dependence of the performance of the system on the blocking P_b parameter. Fig. 6 shows the throughput s versus the total channel loading G for four different P_b values. For comparison, the curve generated from (2) is also plotted as a dashed curve. We observe that for low loading conditions, the throughput level is larger when the system is loaded by multifractal traffic than that attained when the system is loaded by Poisson traffic, irrespective of the blocking probability P_b value. Under high loading conditions, the performance of the system loaded by the LRD traffic process remains much better than that experienced under Poisson traffic

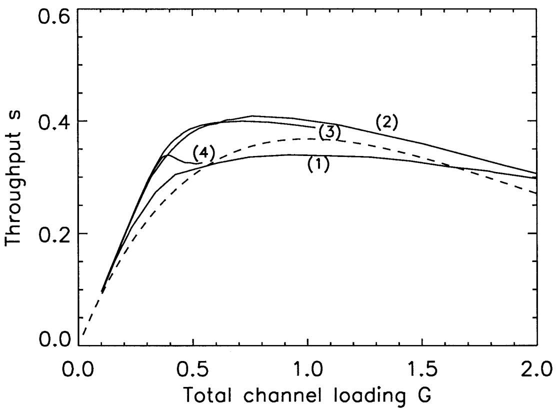

Fig. 6. Throughput s versus total channel loading G curves for the ALOHA system under multifractal traffic with $\alpha = 100$. (1) $P_b = 0.2$, (2) $P_b = 0.4$, (3) $P_b = 0.6$, and (4) $P_b = 0.8$.

loading if suitable P_b values [0.4 and 0.6, corresponding to curves (2) and (3) in Fig. 6] are used. The underlying reason is that the multifractal traffic with this particular burstiness indicator value ($\alpha = 100$) consists of fewer but larger batches of bursts. Since the batches are larger, the multifractal traffic is more bursty than the Poisson traffic. Since the number of bursts is fewer, after those bursts are effectively blocked with quite-high P_b values, the overall throughput of the system is even better than that under Poisson traffic.

It is interesting to note that a good selection of a P_b level under multifractal traffic loading with $\alpha = 100$ is higher than that used under Poisson traffic loading. This higher P_b level ensures that those few but large batches of bursts are immediately blocked once their presence is detected. When the multifractal traffic process becomes more bursty (corresponding to smaller α values), we find that the optimal P_b level has to be increased gradually since the batches are now of larger size and their appearance becomes more frequent.

Fig. 7 shows $N_{\rm Ret}$(90%) versus total channel-loading curves for the four P_b values studied in Fig. 6. We observe that, typically, when the blocking level P_b is increased, the delay performance is improved. In a satellite network, for example, $N_{\rm Ret}$ (90%) is often required to not exceed 2 (or a similarly small value, due to the high retransmission delay involved) for not-too-high loading conditions. Under such a criterion, a value of $P_b = 0.6$ is most preferred. Re-examining Fig. 6, we find that this P_b value also produces good throughput behavior.

Now that we have demonstrated the performance of the system under different values for the T_H, W, and P_b parameters, we study the performance of the system under multifractal traffic-loading processes characterized by different burstiness levels, as expressed by their different corresponding α parameters. Fig. 8 shows the system throughput s versus total channel-loading G performance curves for five different α levels. It is noted distinctively that the attained system throughput behavior critically depends on the selected value for the loading-process burstiness parameter α value, as shown by the curves (1)–(5) in Fig. 8. When the multifractal traffic is not very bursty ($\alpha \geq 100$), the throughput performance of the system under multifractal traffic loading is noted to be much better than that attained under Poisson traffic loading

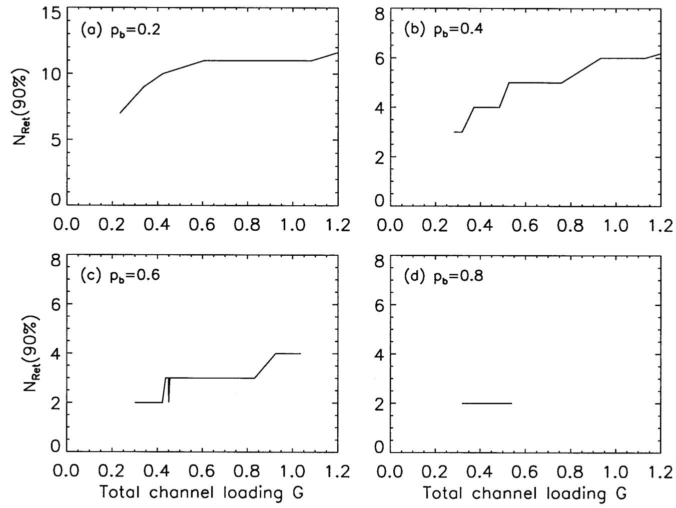

Fig. 7. The 90th percentile of the number of retransmissions versus total channel loading G curves for the system under multifractal traffic with $\alpha = 100$. (a) $P_b = 0.2$, (b) $P_b = 0.4$, (c) $P_b = 0.6$, and (d) $P_b = 0.8$.

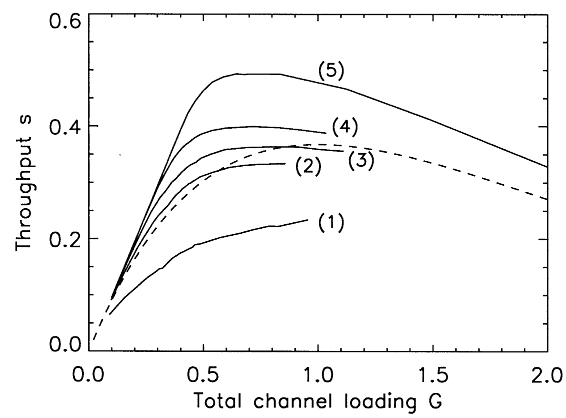

Fig. 8. Throughput s versus total channel-loading G curves for multifractal traffic. The 5 curves, from bottom to top denoted as (1) to (5), correspond to $\alpha = 10$, 30, 50, 100, and 400. The dashed curve is generated from (2).

[curves (4) and (5) of Fig. 8]. However, when the loading LRD traffic process becomes highly bursty, as is the case when we set $\alpha = 30$ or 10, the throughput performance exhibited under multifractal traffic is much worse than that attained under Poisson traffic loading [curves (1) and (2) of Fig. 8]. The underlying reason for the above phenomenon is that when the multifractal traffic process is not too bursty, it only contains quite few big bursts. Thus, most of the time message arrival process is "smoother" than that created by a Poisson process. As a rare burst arrives, blocking takes place. Hence, the overall throughput of the system is even better than that under Poisson traffic. However, when the multifractal traffic becomes too bursty, those big bursts arrive too frequently. While most of them can be blocked so that the system is stable, the throughput of the system is nevertheless much worse than that under Poisson traffic.

The delay performance for the system when loaded by multifractal traffic processes corresponding to the conditions used for Fig. 8 [except for the case corresponding to $\alpha = 100$, which is shown in Fig. 7(c)] is shown in Fig. 9. We observe that, for not-too-high loading conditions, $N_{\rm Ret}$(90%) is less than or

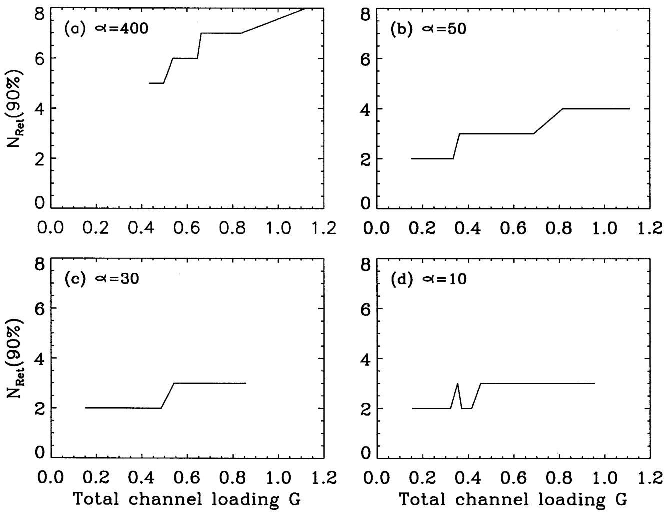

Fig. 9. The 90th percentile of the number of retransmissions versus total channel-loading G curves under multifractal traffic with different α values.

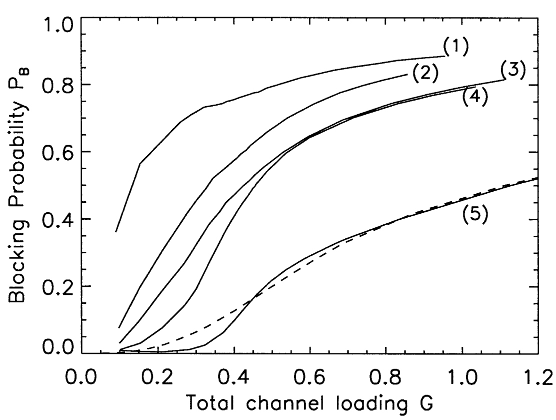

Fig. 10. Blocking probability P_b versus total channel-loading G curves. The 5 solid curves, from top to bottom denoted as (1) to (5), correspond to multifractal traffic processes with $\alpha = 10$, 30, 50, 100, and 400. The dashed curve is for Poisson traffic loading.

equal to 2 [the delay statistics for $\alpha = 400$ for low loading conditions is not sufficient for the computation of $N_{\rm Ret}$ (90%). In other words, such a delay requirement for $\alpha = 400$ is automatically ensured].

Finally, we examine the behavior of the system's attained total blocking probability levels when the system is loaded by a multifractal traffic process under a wide range of burstiness levels. Fig. 10 shows the corresponding blocking-performance results, under the optimal P_b values explained earlier (so that the throughput of the system is highest, while delay is minimal). We observe that the blocking probability is larger when the loading process is burstier, with the blocking level attained for $\alpha = 400$ being similar to that exhibited under Poisson traffic loading. Comparing curves (5) shown in Figs. 8 and 10 with the corresponding curves presented by Aracil and Munoz [13], we conclude that the traffic used in [13] is much less bursty than a multifractal traffic process with $\alpha = 400$.

IV. Conclusion

In this paper, we have studied the performance of a random-access scheme when loaded by LRD traffic-loading processes. The LRD traffic process is modeled as a multiplicative multifractal process. The random-access scheme is the prototypical ALOHA channel with blocking. Five key parameters are introduced to characterize the scheme. We show that the key performance features of the random-access protocols are determined by the burstiness level of the loading traffic process and not solely by its LRD character. We demonstrate that when the LRD loading process is not very bursty, the multiple-access protocol can yield better performance than that exhibited under Poisson loading conditions. In turn, significant performance degradations are observed when the system is loaded by LRD processes characterized by higher levels of burstiness. We further show that the parameters of the protocol must be tuned up carefully to yield efficient performance behavior.

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