

## A BOUND ON THE CAPACITY OF BACKOFF AND ACKNOWLEDGMENT-BASED PROTOCOLS\*

LESLIE ANN GOLDBERG<sup>†</sup>, MARK JERRUM<sup>‡</sup>, SAMPATH KANNAN<sup>§</sup>, AND  
MIKE PATERSON<sup>†</sup>

**Abstract.** We study contention-resolution protocols for multiple-access channels. We show that *every* backoff protocol is transient if the arrival rate,  $\lambda$ , is at least 0.42 and that the capacity of every backoff protocol is at most 0.42. Thus, we show that backoff protocols have (provably) smaller capacity than full-sensing protocols. Finally, we show that the corresponding results, with the larger arrival bound of 0.531, also hold for every acknowledgment-based protocol.

**Key words.** contention-resolution, backoff, multiple-access channel, stability, protocol

**AMS subject classifications.** 68W20, 68W15

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**1. Introduction.** A *multiple-access channel* is a broadcast channel that allows multiple users to communicate with each other by sending messages onto the channel. If two or more users simultaneously send messages, then the messages interfere with each other (collide), and the messages are not transmitted successfully. The channel is not centrally controlled. Instead, the users use a contention-resolution protocol to resolve collisions. Thus, after a collision, each user involved in the collision waits a random amount of time (which is determined by the protocol) before resending.

Following previous work on multiple-access channels, we work in a *time-slotted* model in which time is partitioned into discrete *time steps*. At the beginning of each time step, a random number of messages enter the system, each of which is associated with a new user which has no other messages to send. The number of messages that enter the system is drawn from a Poisson distribution with mean  $\lambda$ . During each time step, each message chooses independently whether to send to the channel. If *exactly* one message sends to the channel during the time step, then this message leaves the system and we call this a *success*. Otherwise, all of the messages remain in the system and the next time step is started. Note that when a message sends to the channel this may or may not result in a success, depending on whether any other messages send to the channel.

The quality of a protocol can be measured in several ways. Typically, one models the execution of the protocol as a Markov chain. If the protocol is good (for a given arrival rate  $\lambda$ ), the corresponding Markov chain will be *recurrent* (with probability 1, it will eventually return to the empty state in which no messages are waiting). Otherwise, the chain is said to be *transient* (and we also say that a protocol is tran-

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<sup>†</sup>Department of Computer Science, University of Warwick, Coventry, CV4 7AL, United Kingdom (<http://www.dcs.warwick.ac.uk/~leslie/>; <http://www.dcs.warwick.ac.uk/~msp/>).

<sup>‡</sup>Division of Informatics, University of Edinburgh, JCMB, The King’s Buildings, Edinburgh EH9 3JZ, United Kingdom (<http://www.dcs.ed.ac.uk/~mrj/>).

<sup>§</sup>Department of Computer and Information Science, University of Pennsylvania, 200 South 33rd St., Philadelphia, PA 19104-6389 (<http://www.cis.upenn.edu/~kannan/>).

sient). Note that transience is a very strong form of instability. In particular, if we focus on any finite set of “good” states, then if the chain is transient, the probability of visiting these states at least  $N$  times during the infinite run of the protocol is exponentially small in  $N$ . (This follows because the relevant Markov chain is irreducible and aperiodic.)

Another way to measure the quality of a protocol is to measure its *capacity*. A protocol is said to achieve *full throughput* at rate  $\lambda$  if, when it is run with input rate  $\lambda$ , the average success rate is  $\lambda$ . The *capacity* of the protocol [4] is the maximum arrival rate at which it achieves full throughput.

The protocols that we consider in this paper are *acknowledgment-based* protocols. In the acknowledgment-based model, the only information that a user receives about the state of the system is the history of its own transmissions. An alternative model is the *full-sensing* model, in which *every* user listens to the channel at *every* step, regardless of whether it sends during the step.<sup>1</sup>

One particularly simple and easy-to-implement class of acknowledgment-based protocols is the class of *backoff protocols*. A backoff protocol is a sequence of probabilities  $p_0, p_1, \dots$ . If a message has sent unsuccessfully  $i$  times before a time step, then, with probability  $p_i$ , it sends during the time step. Otherwise, it does not send. Kelly and MacPhee [13, 14, 17] gave a formula for the *critical arrival rate*,  $\lambda^*$ , of a backoff protocol, which is the minimum arrival rate for which the expected number of successful transmissions that the protocol makes is finite.<sup>2</sup>

Perhaps the best-known backoff protocol is the *binary exponential backoff protocol* in which  $p_i = 2^{-i}$ . This protocol is the basis of the Ethernet protocol of Metcalfe and Boggs [18].<sup>3</sup> Kelly and MacPhee showed that the critical arrival rate of this protocol is  $\ln 2$ . Thus, if  $\lambda > \ln 2$ , then binary exponential backoff achieves only a finite number of successful transmissions (in expectation). Aldous [1] showed that the binary exponential backoff protocol is not a good protocol for *any* positive arrival rate  $\lambda$ . In particular, it is transient and the expected number of successful transmissions in  $t$  steps is  $o(t)$ . MacPhee [17] posed the question of whether there exists a backoff protocol which is recurrent for some positive arrival rate  $\lambda$ .

In this paper, we show that there is no backoff protocol which is recurrent for  $\lambda \geq 0.42$ . (Thus, *every* backoff protocol is transient if  $\lambda \geq 0.42$ .) Also, every backoff protocol has capacity at most 0.42. As far as we know, our result is the first proof showing that backoff protocols have smaller capacity than full-sensing protocols. In particular, Mosely and Humblet [20] have discovered a full-sensing protocol with capacity 0.48776.<sup>4</sup> Finally, we show that *no* acknowledgment-based protocol is recurrent for  $\lambda \geq 0.530045$ .

<sup>1</sup>In practice, it is possible to implement the full-sensing model when there is a single channel, but this becomes increasingly difficult in situations where there are multiple shared channels, such as optical networks. Thus, acknowledgment-based protocols are sometimes preferable to full-sensing protocols. For work on contention-resolution in the multiple-channel setting, see [6].

<sup>2</sup>If  $\lambda > \lambda^*$ , then the expected number of successes is finite, even if the protocol runs forever. They showed that the critical arrival rate is 0 if the expected number of times that a message sends during the first  $t$  steps is  $\omega(\log t)$ .

<sup>3</sup>There are several differences between the “real-life” Ethernet protocol and “pure” binary exponential backoff, but we do not describe these here.

<sup>4</sup>Mosely and Humblet’s protocol is a “tree protocol” in the sense of Capetanakis [3] and Tsybakov and Mikhailov [25]. For a simple analysis of the protocol, see [26]. Vvedenskaya and Pinsker have shown how to modify Mosely and Humblet’s protocol to achieve an improvement in the capacity (in the seventh decimal place) [27].

**1.1. Related work.** Backoff protocols and acknowledgment-based protocols have also been studied in an  $n$ -user model, which combines contention-resolution with queueing. In this model, it is assumed that  $n$  users maintain queues of messages, and that new messages arrive at the tails of the queues. At each step, the users use contention-resolution protocols to try to send the messages at the heads of their queues. It turns out that the queues have a stabilizing effect, so some protocols (such as “polynomial backoff”) which are unstable in our model [14] are stable in the queueing model [12]. We will not describe queueing-model results here but refer the reader to [2, 9, 12, 22].

Much work has gone into determining upper bounds on the capacity that can be achieved by a full-sensing protocol. The current best result is due to Tsybakov and Likhanov [24], who have shown that no protocol can achieve capacity higher than 0.568. (For more information, see [4, 10, 19, 23].) In the full-sensing model, one typically assumes that messages are born at real “times” which are chosen uniformly from the unit interval. Recently, Loher [15, 16] has shown that if a protocol is required to respect these birth times, in the sense that packets must be successfully delivered in their birth order, then no protocol can achieve capacity higher than 0.4906. Intuitively, the “first-come-first-served” restriction seems very strong, so it is somewhat surprising that the best-known algorithm without the restriction (that of Vvedenskaya and Pinsker) does not beat this upper bound. The algorithm of Humblet and Mosely satisfies the first-come-first-served restriction.

**2. Markov chain background.** A Markov chain  $X = \{X_0, X_1, \dots\}$  with a countable state space  $\Omega$  (see [11]) is *time-homogeneous* if its transition probabilities are independent of time so  $\Pr(X_{n+1} = j \mid X_n = i) = \Pr(X_1 = j \mid X_0 = i)$  for all  $n, i, j$ . It is *irreducible* if every pair  $(i, j)$  of states is connected in the sense that there is an  $n > 0$  such that  $\Pr(X_{n+m} = j \mid X_m = i) > 0$ . It is *aperiodic* if every state  $i$  satisfies  $\gcd\{n \mid \Pr(X_{n+m} = i \mid X_m = i) > 0\} = 1$ . If the chain is irreducible and aperiodic, then we say that it is *recurrent* if it returns to its start state with probability 1. That is, it is recurrent if for some state  $i$  (and therefore for all  $i$ ),  $\text{Prob}[X_t = i \text{ for some } t \geq 1 \mid X_0 = i] = 1$ . Otherwise,  $X$  is said to be *transient*.  $X$  is *positive recurrent* (or ergodic) if the expected number of steps that it takes before returning to its start state is finite. A chain is positive recurrent if and only if it has a unique stationary distribution. The standard way to prove that a Markov chain is positive recurrent is Foster’s theorem.

**THEOREM 1** (Foster [7]). *A time-homogeneous irreducible aperiodic Markov chain  $X$  with a countable state space  $\Omega$  is positive recurrent if and only if there exists a positive function  $f(\rho)$ ,  $\rho \in \Omega$ , a number  $\epsilon > 0$ , and a finite set  $\mathcal{A} \subseteq \Omega$  such that the following inequalities hold:*

$$(1) \quad E[f(X(t+1)) - f(X(t)) \mid X(t) = \rho] \leq -\epsilon, \quad \rho \notin \mathcal{A},$$

$$(2) \quad E[f(X(t+1)) \mid X(t) = \rho] < \infty, \quad \rho \in \mathcal{A}.$$

Basically, the idea is to use a “potential function”  $f$  to follow the progress of the chain. The chain is positive recurrent if and only if there is a potential function  $f$  which

1. usually decreases (equation (1)), and
2. cannot increase much (equation (2))

in a single step. Equation (1) implies that, from any state  $\rho \notin \mathcal{A}$ , the expected time to reach  $\mathcal{A}$  from  $\rho$  is at most  $f(\rho)/\epsilon$ . This (combined with (2)) implies that the expected return time to  $\mathcal{A}$  is finite, which in turn implies that the chain is positive recurrent.

(For more details, see [5].) Theorems like Theorem 1 are called “drift theorems” because the progress of the Markov chain  $X$  is studied by focusing on the “drift” of the potential function  $f$ . The function  $f$  is sometimes called a *Lyapunov function* or a *test function*.

We can also use drift theorems to show that a Markov chain is *not* positive recurrent. To do this we want to find a potential function  $f$  which “drifts” towards larger potentials. Here is the theorem that we will use.

**THEOREM 2** (Fayolle, Malyshev, and Menshikov [5]). *An irreducible aperiodic time-homogeneous Markov chain  $X$  with countable state space  $\Omega$  is not positive recurrent if there is a function  $f$  with domain  $\Omega$  and there are constants  $C$  and  $d$  such that*

1. *there is a state  $x$  with  $f(x) > C$ , and a state  $y$  with  $f(y) \leq C$ ,*
2.  *$E[f(X_1) - f(X_0) \mid X_0 = x] \geq 0$  for all  $x$  with  $f(x) > C$ , and*
3.  *$E[|f(X_1) - f(X_0)| \mid X_0 = x] \leq d$  for every state  $x$ .*

We will use a similar theorem to show that a Markov chain is transient (which is stronger than saying that it is not positive recurrent).

**THEOREM 3** (Fayolle, Malyshev, and Menshikov [5]). *An irreducible aperiodic time-homogeneous Markov chain  $X$  with countable state space  $\Omega$  is transient if there is a positive function  $f$  with domain  $\Omega$  and there are positive constants  $C$ ,  $d$ , and  $\varepsilon$  such that*

1. *there is a state  $x$  with  $f(x) > C$ , and a state  $y$  with  $f(y) \leq C$ ,*
2.  *$E[f(X_1) - f(X_0) \mid X_0 = x] \geq \varepsilon$  for all  $x$  with  $f(x) > C$ , and*
3. *if  $|f(x) - f(y)| > d$ , then the probability of moving from  $x$  to  $y$  in a single move is 0.*

**3. Stochastic domination and monotonicity.** Suppose that  $X$  is a Markov chain and that the (countable) state space  $\Omega$  of the chain is a *partial order* with binary relation  $\leq$ . If  $A$  and  $B$  are random variables taking states as values, then  $B$  *dominates*  $A$  if and only if there is a joint sample space for  $A$  and  $B$  in which the value of  $A$  is always less than or equal to the value of  $B$ . Note that there will generally be other joint sample spaces in which the value of  $A$  can exceed the value of  $B$ . We write  $A \leq B$  to indicate that  $B$  dominates  $A$ . We say that  $X$  is *monotonic* if for any states  $x \leq x'$ , the next state conditioned on starting at  $x'$  dominates the next state conditioned on starting at  $x$ . (Formally,  $(X_1 \mid X_0 = x')$  dominates  $(X_1 \mid X_0 = x)$ .)

When an acknowledgment-based protocol is viewed as a Markov chain, the state is just the collection of messages in the system. (Each message is identified by the history of its transmissions.) Thus, the state space is countable and forms a partial order with respect to the subset inclusion relation  $\subseteq$  (for multisets). We say that a protocol is *deletion resilient* [8] if its Markov chain is monotonic with respect to the subset-inclusion partial order.

**OBSERVATION 4.** *Every acknowledgment-based protocol is deletion resilient.*

*Proof.* Consider the states  $x$  and  $x'$  with  $x \subseteq x'$ . Recall that each state is a set of messages, each message being identified by its transmission history. Thus,  $x'$  contains all of the messages in  $x$  and possibly others. Now consider one step of the protocol. We wish to show that the random variable denoting the next state  $z' = (X_1 \mid X_0 = x')$  dominates the random variable  $z = (X_1 \mid X_0 = x)$ .  $z'$  does dominate  $z$  because we can draw  $z$  and  $z'$  from a joint sample space in which

- the messages in  $x$  do the same thing in both copies, and
- both copies have the same number of new arrivals, which make the same number of send attempts in both copies.

Now consider any message  $m$  which is either a new arrival or a member of  $x$ .

1. If  $m$  is silent during the step, then its transmission history in  $z'$  is the same as in  $z$ .
2. If  $m$  has a collision during the transition to  $z$ , then it also has a collision during the transition to  $z'$ , so its transmission history in  $z'$  is the same as in  $z$ .

Thus,  $z \subseteq z'$ .  $\square$

As we indicated earlier, we will generally assume that the number of messages entering the system at a given step is drawn from a Poisson process with mean  $\lambda$ . However, it will sometimes be useful to consider other message-arrival distributions. If  $I$  and  $I'$  are message-arrival distributions, we write  $I \leq I'$  to indicate that the number of messages generated under  $I$  is dominated by the number of messages generated under  $I'$ .

**OBSERVATION 5.** *If the acknowledgment-based protocol  $P$  is recurrent under the message-arrival distribution  $I'$  and  $I \leq I'$ , then  $P$  is also recurrent under  $I$ .*

*Proof.* Let  $X$  be the Markov chain corresponding to protocol  $P$  with arrival distribution  $I$  with  $X_0$  as the empty state. Let  $X'$  be the analogous Markov chain with arrival distribution  $I'$ . Consider the evolution of the stochastic process  $(X_0, X'_0), (X_1, X'_1), \dots$ . We will choose the random variable  $(X_i, X'_i)$  from a joint probability distribution in which

1. every message which is common to  $X_i$  and  $X'_i$  does the same thing in both copies;
2. the new arrivals which are drawn from  $I$  arrive in both copies and make the same number of send attempts in both copies;
3. some additional messages may arrive in  $X'_i$  (according to  $I'$ ).

Note that items (2) and (3) are possible since  $I \leq I'$ . We can now show by induction on  $t$  that  $X'_t$  dominates  $X_t$ . That is, when this joint distribution is used,  $X_t$  is a subset of  $X'_t$ . This holds for  $t = 0$  since  $X_0 = X'_0$ . The inductive step is the same as in the proof of Observation 4. Consider any message  $m$  which is in  $X_t$  or arrives (according to  $I$ ) just before step  $t + 1$ .

1. If  $m$  is silent during the step, then its transmission history in  $X'_{t+1}$  is the same as in  $X_{t+1}$ .
2. If  $m$  has a collision during the transition to  $X_{t+1}$ , then it also has a collision during the transition to  $X'_{t+1}$ .

Thus,  $X_{t+1} \subseteq X'_{t+1}$ . Finally, since  $X'_t$  dominates  $X_t$ , the recurrence of  $X'_t$  implies the recurrence of  $X_t$ .  $\square$

**4. Backoff protocols.** In this section, we will show that there is no backoff protocol which is recurrent for  $\lambda \geq 0.42$ . Our method will be to use the drift theorems in section 2. Let  $p_0, p_1, \dots$  be a backoff protocol. Without loss of generality, we can assume  $p_0 = 1$ , since we can ignore new arrivals until they first send.<sup>5</sup> Let  $\lambda = 0.42$ . Let  $X$  be the Markov chain described in section 3 which describes the behavior of the protocol with arrival rate  $\lambda$ . First, we will construct a potential function (Lyapunov function)  $f$  which satisfies the conditions of Theorem 2, that is, a potential function which has a bounded positive drift. We will use Theorem 2 to conclude that the chain is not positive recurrent. Next, we will consider the behavior of the protocol under a *truncated* arrival distribution, and we will use Theorem 3 to show that the protocol

<sup>5</sup>Since the arrivals are Poisson, and Poisson random variables are additive, the number of messages making their very first send on a given time step is Poisson, and the mean of this distribution approaches  $\lambda$ .

is transient. Using Observation 5 (domination), we will conclude that the protocol is also transient with Poisson arrivals at rate  $\lambda$  or higher. Finally, we will show that the *capacity* of every backoff protocol is at most 0.42.

We will use the following technical lemma.

LEMMA 6. *Let  $1 \leq t_i \leq d$  for  $i \in [1, k]$  and  $\prod_{i=1}^k t_i = c$ . Then  $\sum_{i=1}^k (t_i - 1) \leq (d - 1) \frac{\log c}{\log d}$ .*

*Proof.* Let  $S = \sum_{i=1}^k t_i$ .  $S$  can be viewed as a function of  $k - 1$  of the  $t_i$ 's; for example,  $S = \sum_{i=1}^{k-1} t_i + c / \prod_{i=1}^{k-1} t_i$ . For  $i \in \{1, \dots, k - 1\}$ , the derivative of  $S$  with respect to  $t_i$  is  $1 - c / (t_i \prod_{j=1}^{k-1} t_j)$ . Thus, the derivative is positive if  $t_i > t_k$ . Thus,  $S$  is maximized (subject to  $c$ ) by setting some  $t_i$ 's to 1, some  $t_i$ 's to  $d$ , and at most one  $t_i$  to some intermediate value  $t \in [1, d)$ . Given this, the maximum value of  $\sum_{i=1}^k (t_i - 1)$  is  $s(d - 1) + t - 1$ , where  $c = d^s t$  and  $s = \lfloor (\log c) / (\log d) \rfloor$ . Let  $\alpha$  be the fractional part of  $(\log c) / (\log d)$ , that is,  $\alpha = (\log c) / (\log d) - s$ . We want to show that  $s(d - 1) + t - 1 \leq (d - 1)(\log c) / (\log d)$ . This is true, since

$$\begin{aligned} (d - 1) \frac{\log c}{\log d} - s(d - 1) - (t - 1) &= \alpha(d - 1) - c/d^s + 1 \\ &= \alpha(d - 1) - d^\alpha + 1 \\ &\geq 0. \end{aligned}$$

The final inequality holds since we have equality for  $d = 1$ , and the partial derivative with respect to  $d$  proves that the inequality holds for  $d > 1$ .  $\square$

We now define some parameters of a state  $x$ . Let  $k(x)$  denote the number of messages in state  $x$ . If  $k(x) = 0$ , then  $p(x) = r(x) = u(x) = 0$ . Otherwise, let  $m_1, \dots, m_{k(x)}$  denote the messages in state  $x$ , with send probabilities  $\rho_1 \geq \dots \geq \rho_{k(x)}$ . Let  $p(x) = \rho_1$  and let  $r(x)$  denote the probability that at least one of  $m_2, \dots, m_{k(x)}$  sends on the next step. Let  $u(x)$  denote the probability that exactly one of  $m_2, \dots, m_{k(x)}$  sends on the next step. Clearly  $u(x) \leq r(x)$ . If  $p(x) < r(x)$ , then we use the following (tighter) upper bound for  $u(x)$ .

LEMMA 7. *If  $p(x) < r(x)$ , then  $u(x) \leq \frac{r(x) - r(x)^2/2}{1 - p(x)/2}$ .*

*Proof.* Fix a state  $x$ . We will use  $k, p, r, \dots$  to denote  $k(x), p(x), r(x), \dots$ . Since  $p < r$ , we have  $k \geq 2$ .

$$u = \sum_{i=2}^k \frac{\rho_i}{1 - \rho_i} \prod_{i=2}^k (1 - \rho_i) = \sum_{i=2}^k (t_i - 1)(1 - r),$$

where  $t_i = 1 / (1 - \rho_i)$ . Let  $d = 1 / (1 - p)$ , and note that  $1 \leq t_i \leq d$ . By Lemma 6

$$\begin{aligned} u &\leq (1 - r)(d - 1) \frac{\log(\prod_{i=2}^k t_i)}{\log d} = (1 - r) \frac{p}{1 - p} \frac{\log(1 / (1 - r))}{\log d} \\ &= (1 - r) \frac{p}{1 - p} \frac{(-\log(1 - r))}{(-\log(1 - p))}. \end{aligned}$$

Now we wish to show that

$$(1 - r) \frac{p}{1 - p} \frac{(-\log(1 - r))}{(-\log(1 - p))} \leq \frac{r - r^2/2}{1 - p/2},$$

i.e., that

$$(1 - r) \frac{(-\log(1 - r))}{r - r^2/2} \leq (1 - p) \frac{(-\log(1 - p))}{p - p^2/2}.$$

This is true, since the function  $(1 - r) \frac{(-\log(1-r))}{r-r^2/2}$  is decreasing in  $r$ . To see this, note that the derivative of this function with respect to  $r$  is  $y(r)/(r - r^2/2)^2$ , where

$$\begin{aligned} y(r) &= (1 - r + r^2/2) \log(1 - r) + (r - r^2/2) \\ &\leq (1 - r + r^2/2)(-r - r^2/2) + (r - r^2/2) = -r^4/4. \quad \square \end{aligned}$$

Let  $\mathcal{S}(x)$  denote the probability that there is a success when the system is run for one step starting in state  $x$ . (Recall that a success occurs if *exactly* one message sends during the step. This single sender might be a new arrival, or it might be an old message from state  $x$ .) Let

$$g(r, p) = e^{-\lambda} \left[ (1 - r)p + (1 - p) \min \left\{ r, \frac{r - r^2/2}{1 - p/2} \right\} + (1 - p)(1 - r)\lambda \right].$$

We now have the following corollary of Lemma 7.

COROLLARY 8. *For any state  $x$ ,  $\mathcal{S}(x) \leq g(r(x), p(x))$ .*

Let  $s(x)$  denote the probability that at least one message in state  $x$  sends on the next step. That is,  $s(x)$  is the probability that at least one *existing* message in  $x$  sends. New arrivals may also send. There may or may not be a success. (Thus, if  $x$  is the empty state, then  $s(x) = 0$ .) Let  $A = 0.9$  and  $B = 0.41$ . For every  $z \in [0, 1]$ , let  $c(z) = \max(0, -Az + B)$ . For every state  $x$ , let  $f(x) = k(x) + c(s(x))$ . The function  $f$  is the potential function alluded to earlier, which plays a leading role in Theorems 2 and 3. To a first approximation,  $f(x)$  counts the number of messages in the state  $x$ , but the small correction term is crucial. Finally, let

$$h(r, p) = \lambda - g(r, p) - [1 - e^{-\lambda}(1 - p)(1 - r)(1 + \lambda)]c(r + p - rp) + e^{-\lambda}p(1 - r)c(r).$$

Now we have the following.

OBSERVATION 9. *For any state  $x$ ,  $E[|f(X_1) - f(X_0)| \mid X_0 = x] \leq 1 + B$ .*

LEMMA 10. *For any state  $x$ ,  $E[f(X_1) - f(X_0) \mid X_0 = x] \geq h(r(x), p(x))$ .*

*Proof.* The result follows from the following chain of inequalities, each link of which is justified below:

$$\begin{aligned} &E[f(X_1) - f(X_0) \mid X_0 = x] \\ &= \lambda - \mathcal{S}(x) + E[c(s(X_1)) \mid X_0 = x] - c(s(x)) \\ &\geq \lambda - g(r(x), p(x)) + E[c(s(X_1)) \mid X_0 = x] - c(s(x)) \\ &\geq \lambda - g(r(x), p(x)) + e^{-\lambda}(1 - p(x))(1 - r(x))(1 + \lambda)c(s(x)) \\ &\quad + e^{-\lambda}p(x)(1 - r(x))c(r(x)) - c(s(x)) \\ &= h(r(x), p(x)). \end{aligned}$$

The first inequality follows from Corollary 8. The second comes from substituting exact expressions for  $c(s(X_1))$  whenever the form of  $X_1$  allows it, and using the bound  $c(s(X_1)) \geq 0$  elsewhere. If none of the existing messages sends and there is at most one arrival, then  $c(s(X_1)) = c(s(x))$ , giving the third term; if message  $m_1$  alone sends and there are no new arrivals, then  $c(s(X_1)) = c(r(x))$ , giving the fourth term. The final equality uses the fact that  $s(x) = p(x) + r(x) - p(x)r(x)$ .  $\square$

LEMMA 11. *For any  $r \in [0, 1]$  and  $p \in [0, 1]$ ,  $h(r, p) \geq 0.003$ .*

*Proof.* We defer the proof of this lemma to the appendix. Figure 1 contains a (Mathematica-produced) plot of  $-h(r, p)$  over the range  $r \in [0, 1]$ ,  $p \in [0, 1]$ . The plot suggests that  $-h(r, p)$  is bounded below zero.

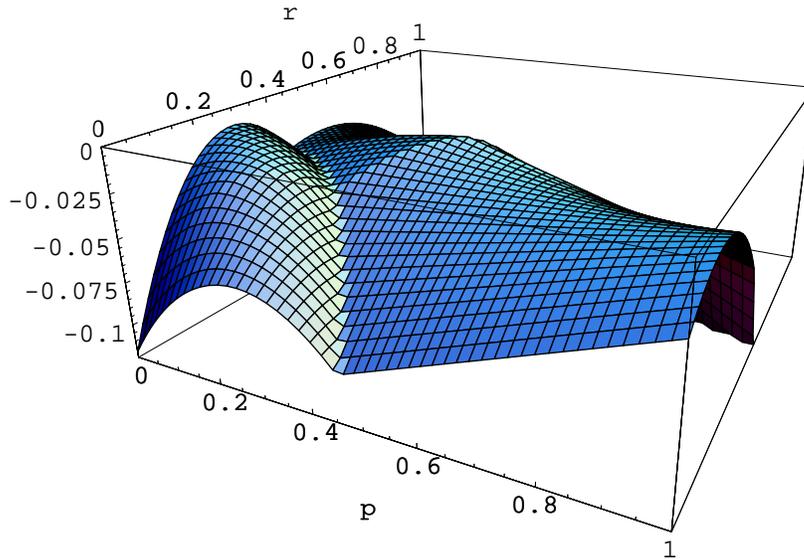


FIG. 1.  $-h(r, p)$  over the range  $r \in [0, 1]$ ,  $p \in [0, 1]$ .

We note here that our proof of the lemma (in the appendix) involves evaluating certain polynomials at about 40,000 points, and we did this using Mathematica.  $\square$

We now have the following theorem.

**THEOREM 12.** *No backoff protocol is positive recurrent when the arrival rate is  $\lambda = 0.42$ .*

*Proof.* This follows from Theorem 2, Observation 9, and Lemmas 10 and 11. The value  $C$  in Theorem 2 can be taken to be 1 and the value  $d$  can be taken to be  $1 + B$ .  $\square$

Now we wish to show that every backoff protocol is transient for  $\lambda \geq 0.42$ . Once again, fix a backoff protocol  $p_0, p_1, \dots$  with  $p_0 = 1$ . Notice that our potential function  $f$  almost satisfies the conditions in Theorem 3. The main problem is that there is no absolute bound on the amount that  $f$  can change in a single step, because the arrivals are drawn from a Poisson distribution. We get around this problem by first considering a *truncated-Poisson* distribution,  $T_{M, \lambda}$ , in which the probability of  $r$  inputs is  $e^{-\lambda} \lambda^r / r!$  (as for the Poisson distribution) when  $r < M$ , but  $r = M$  for the remaining probability. By choosing  $M$  sufficiently large we can have  $E[T_{M, \lambda}]$  arbitrarily close to  $\lambda$ .

**LEMMA 13.** *Every backoff protocol is transient for the input distribution  $T_{M, \lambda}$  when  $\lambda = 0.42$  and  $\lambda' = E[T_{M, \lambda}] > \lambda - 0.001$ .*

*Proof.* The proof is almost identical to that of Theorem 12, except that the first term,  $\lambda$ , in the definition of  $h(r, p)$  (for Lemmas 10 and 11) must be replaced by  $\lambda'$ . The corresponding function  $h'$  satisfies  $h'(r, p) \geq h(r, p) - 0.001$ . Thus Lemma 11 shows that  $h'(r, p) \geq 0.002$  for all  $r \in [0, 1]$  and  $p \in [0, 1]$ .

The potential function  $f(x)$  is defined as before, but under the truncated input distribution we have the property required for Theorem 3. If  $|f(x) - f(y)| > M + B$ , then the probability of moving from  $x$  to  $y$  in a single move is 0.

The lemma follows from Theorem 3, where the values of  $C$ ,  $\varepsilon$ , and  $d$  can be taken to be 1, 0.002, and  $M + B$ , respectively.  $\square$

We now have the following theorem.

**THEOREM 14.** *Every backoff protocol is transient under the Poisson distribution with arrival rate  $\lambda \geq 0.42$ .*

*Proof.* The proof is immediate from Lemma 13 and Observation 5.  $\square$

Finally, we bound the capacity of every backoff protocol.

**THEOREM 15.** *The capacity of every backoff protocol is at most 0.42.*

*Proof.* Let  $p_0, p_1, \dots$  be a backoff protocol, let  $\lambda'' \geq 0.42$  be the arrival rate, and let  $\lambda = 0.42$ . View the arrivals at each step as  $\text{Poisson}(\lambda)$  “ordinary” messages and  $\text{Poisson}(\lambda'' - \lambda)$  “ghost” messages. We will show that the protocol does not achieve average success rate  $\lambda''$ . Let  $Y_0, Y_1, \dots$  be the Markov chain describing the protocol. Let  $k(Y_t)$  be the number of ordinary messages in the system after  $t$  steps. Clearly, the expected number of successes in the first  $t$  steps is at most  $\lambda''t - E[k(Y_t)]$ . Now let  $X_1, X_2, \dots$  be the Markov chain describing the evolution of the backoff protocol with arrival rate  $\lambda$  (with no ghost messages). By deletion resilience (Observation 4),  $E[k(Y_t)] \geq E[k(X_t)]$ . Now by Lemmas 10 and 11,  $E[k(X_t)] \geq E[f(X_t)] - B \geq 0.003t - B$ . Thus, the expected number of successes in the first  $t$  steps is at most  $(\lambda'' - 0.003)t + B$ , which is less than  $\lambda''t$  if  $t$  is sufficiently large. (If  $X_0$  is the empty state, then we do not require  $t$  to be sufficiently large, because  $E[f(X_t)] \geq 0.003t + B$ .)  $\square$

**4.1. Improvements.** We choose  $\lambda = 0.42$  in order to make the proof of Lemma 11 (see the appendix) as simple as possible. The lemma seems to be true for  $\lambda$  down to about 0.41 and presumably the parameters  $A$  and  $B$  could be tweaked to get  $\lambda$  slightly smaller.

**5. Acknowledgment-based protocols.** We will prove that every acknowledgment-based protocol is transient for all  $\lambda > 0.531$ ; see Theorem 21 for a precise statement of this claim.

An acknowledgment-based protocol can be viewed as a system which, at every step  $t$ , decides which subset of the old messages to send. The decision is a probabilistic one dependent on the histories of the messages held. As a technical device for proving our bounds, we introduce the notion of a “genie,” which (in general) has more freedom in making these decisions than a protocol.

Since we consider only acknowledgment-based protocols, the behavior of each new message is independent of the other messages and of the state of the system until after its first send. This is why we ignore new messages until their first send—for Poisson arrivals this is equivalent to the convention that each message sends at its arrival time.

A *genie* is a random variable over the natural numbers, dependent on the complete history (of arrivals and sends of messages) up to time  $t - 1$ , which gives a natural number representing the number of messages that the genie will send at time  $t$ . Note that the number of messages that the genie sends at step  $t$  is independent of the number of newly arriving messages which send at step  $t$ . Also, the genie may send any number of messages at step  $t$ —possibly even more than the number of messages that arrived during steps  $1, \dots, t - 1$ . It is clear that for every acknowledgment-based protocol there is a corresponding genie. However, there are genies which do not behave like any protocol; e.g., a genie may give a cumulative total number of “sends” up to time  $t$  which exceeds the actual number of arrivals up to that time.

First, we consider the class of all genies. In Lemma 16, we show that if the arrival rate,  $\lambda$ , exceeds 0.567, then the backlog of messages (the difference between the cumulative number of arrivals and the cumulative number of successes) tends to infinity as time goes on. This implies that no genie has capacity greater than 0.567.

To get a better result, we consider a constrained class of genies called bucket genies. An ordinary genie (as defined previously) has no control over new inputs making their first send but has complete control over any other messages. (In particular, it can even send a message if none has arrived.) A bucket genie has no control over new inputs or over the “bucket” of messages that have already tried exactly once but has complete control over any other messages. We consider a particular type of bucket genie called an “eager” bucket genie. In Lemma 18 we show that for  $\lambda \geq 0.531$ , the backlog tends to infinity for eager bucket genies. In Lemma 19 we show how any bucket genie (including the acknowledgment-based protocol under consideration) can be coupled with an eager bucket genie in such a way that the arbitrary bucket genie doesn’t have many more successes than the eager bucket genie. This, combined with Lemma 16 (which shows that the eager genie doesn’t have enough successes), proves the theorem.

Let  $I(t), G(t)$  be the number of arrivals and the genie’s send value, respectively, at step  $t$ . It is convenient to introduce some indicator variables to express various outcomes at the step under consideration. We use  $i_0, i_1$  for the events of no new arrival, or exactly one arrival, respectively, and  $g_0, g_1$  for the events of no send and exactly one send from the genie. The indicator random variable  $S(t)$  for a success at time  $t$  is given by  $S(t) = i_0g_1 + i_1g_0$ . Let  $\text{In}(t) = \sum_{j \leq t} I(j)$  and  $\text{Out}(t) = \sum_{j \leq t} S(j)$ . Define  $\text{Backlog}(t) = \text{In}(t) - \text{Out}(t)$ . Let  $\lambda = \lambda_0 \approx 0.567$  be the (unique) root of  $\lambda = e^{-\lambda}$ .

LEMMA 16. *For any genie and input rate  $\lambda > \lambda_0$ , there exists  $\varepsilon > 0$  such that*

$$\text{Prob}[\text{Backlog}(t) > \varepsilon t \text{ for all } t \geq T] \rightarrow 1 \text{ as } T \rightarrow \infty.$$

*Proof.* Let  $3\varepsilon = \lambda - e^{-\lambda} > 0$ . At any step  $t$ ,  $S(t)$  is a Bernoulli variable with expectation  $0, e^{-\lambda}, \lambda e^{-\lambda}$ , according to whether  $G(t) > 1, G(t) = 1, G(t) = 0$ , respectively, which is dominated by the Bernoulli variable with expectation  $e^{-\lambda}$ . Therefore  $E[\text{Out}(t)] \leq e^{-\lambda}t$ , and also  $\text{Prob}[\text{Out}(t) - e^{-\lambda}t < \varepsilon t \text{ for all } t \geq T] \rightarrow 1$  as  $T \rightarrow \infty$ . (To see this note that, by a Chernoff bound,  $\text{Prob}[\text{Out}(t) - e^{-\lambda}t \geq \varepsilon t] \leq e^{-\delta t}$  for a positive constant  $\delta$ . Thus,

$$\text{Prob}[\exists t \geq T \text{ such that } \text{Out}(t) - e^{-\lambda}t \geq \varepsilon t] \leq \sum_{t \geq T} e^{-\delta t},$$

which goes to 0 as  $T$  goes to  $\infty$ .)

We also have  $E[\text{In}(t)] = \lambda t$  and  $\text{Prob}[\lambda t - \text{In}(t) \leq \varepsilon t \text{ for all } t \geq T] \rightarrow 1$  as  $T \rightarrow \infty$ , since  $\text{In}(t) = \text{Poisson}(\lambda t)$ .

Since

$$\begin{aligned} \text{Backlog}(t) &= \text{In}(t) - \text{Out}(t) \\ &= (\lambda - e^{-\lambda})t + (\text{In}(t) - \lambda t) + (e^{-\lambda}t - \text{Out}(t)) \\ &= \varepsilon t + (\varepsilon t + \text{In}(t) - \lambda t) + (\varepsilon t + e^{-\lambda}t - \text{Out}(t)), \end{aligned}$$

the result follows.  $\square$

COROLLARY 17. *No acknowledgment-based protocol is recurrent for  $\lambda > \lambda_0$  or has capacity greater than  $\lambda_0$ .*

To strengthen the above result we introduce a restricted class of genies. We think of the messages which have failed exactly once as being contained in *the bucket*. (More generally, we could consider an array of buckets, where the  $j$ th bucket contains those messages which have failed exactly  $j$  times.) A *1-bucket genie*, here called simply

a *bucket genie*, is a genie which simulates a given protocol for the messages in the bucket and is required to choose a send value which is at least as great as the number of sends from the bucket. Thus, on a given step, some number, say  $b$ , of the messages in the bucket will decide to send. Each of these decisions is made independently by each message, which is simulating the protocol. Then the genie will choose a number  $x \geq b$ , which is the number of sends that it will make. As before,  $g_0$  is the indicator for  $x = 0$  and  $g_1$  is the indicator for  $x = 1$ . The indicator for success is  $S(t) = i_0g_1 + i_1g_0$ . At the end of the step, the  $b$  messages from the bucket which have sent leave the bucket. Also, any new arrivals which have collided join the bucket. Note that if the messages in the bucket decide not to send (i.e.,  $b = 0$ ) and there are no new arrivals (i.e.,  $i_0 = 1$ ), then  $S(t)$  can be either 1 or 0, depending on whether or not  $x = 1$ . No matter what  $x$  is, no messages enter or leave the bucket during this step. For such constrained genies, we can improve the bound of Corollary 17.

For the range of arrival rates we consider, an excellent strategy for a genie is to ensure that at least one message is sent at each step. Of course a bucket genie has to respect the bucket messages and is obliged sometimes to send more than one message (inevitably failing). An *eager* genie always sends at least one message, but otherwise sends as few as possible. In particular, it sends  $x = \min(1, b)$ .

An eager bucket genie is easy to analyze, since every arrival is blocked by the genie and enters the bucket.

Let  $\lambda = \lambda_1 \approx 0.531$  be the (unique) root of  $\lambda = (1 + \lambda)e^{-2\lambda}$ .

LEMMA 18. *For any eager bucket genie and input rate  $\lambda > \lambda_1$ , there exists  $\varepsilon > 0$  such that*

$$\text{Prob}[\text{Backlog}(t) > \varepsilon t \text{ for all } t \geq T] \rightarrow 1 \text{ as } T \rightarrow \infty.$$

*Proof.* Let *Eager* be an eager bucket genie. Let  $r_i$  be the probability that a message in the bucket sends for the first time (and hence exits from the bucket)  $i$  steps after its arrival. Assume  $\sum_{i=1}^{\infty} r_i = 1$ ; otherwise there is a positive probability that the message never exits from the bucket, and the result follows trivially.

The generating function for the Poisson distribution with rate  $\lambda$  is  $e^{\lambda(z-1)}$  (i.e., the coefficient of  $z^k$  in this function gives the probability of exactly  $k$  arrivals; see, e.g., [11]). Consider the sends from the bucket at step  $t$ . Since *Eager* always blocks arriving messages, the generating function for messages entering the bucket  $i$  time steps in the past,  $1 \leq i \leq t$ , is  $e^{\lambda(z-1)}$ . Some of these messages may send at step  $t$ ; the generating function for the number of sends is  $e^{\lambda((1-r_i)+r_i z-1)} = e^{\lambda r_i(z-1)}$ . Finally, the generating function for all sends from the bucket at step  $t$  is the convolution of all these functions, i.e.,

$$\prod_{i=1}^t \exp(\lambda r_i(z-1)) = \exp \left[ \lambda(z-1) \sum_{i=1}^t r_i \right].$$

For any  $\delta > 0$ , we can choose  $t$  sufficiently large so that  $\sum_{i=1}^t r_i > 1 - \delta$ . The number of sends from the bucket at step  $t$  is distributed as  $\text{Poisson}(\lambda')$ , where  $(1 - \delta)\lambda < \lambda' \leq \lambda$ . The number of new arrivals sending at step  $t$  is independently  $\text{Poisson}(\lambda)$ . The only situation in which a message succeeds under *Eager* is when there are no new arrivals and the number of sends from the bucket is zero or one. Thus the success probability at step  $t$  is  $e^{-\lambda}e^{-\lambda'}(1 + \lambda')$ . For sufficiently small  $\delta$ , we have  $\lambda_1 < \lambda' \leq \lambda$ , and so  $e^{-\lambda'}(1 + \lambda') < e^{-\lambda_1}(1 + \lambda_1) = e^{\lambda_1} \lambda_1 < e^{\lambda} \lambda$ . Hence  $e^{-\lambda}e^{-\lambda'}(1 + \lambda') \leq \lambda - 3\epsilon$  for  $\epsilon$  sufficiently small. Thus the success event is dominated

by a Bernoulli variable with expectation  $\lambda - 3\epsilon$ . Hence, as in the previous lemma,

$$\text{Prob}[\text{Backlog}(t) > \epsilon t \text{ for all } t \geq T] \rightarrow 1 \text{ as } T \rightarrow \infty,$$

completing the proof.  $\square$

Let *Any* be an arbitrary bucket genie and let *Eager* be the eager bucket genie based on the same bucket parameters. We may couple the executions of *Eager* and *Any* so that the same arrival sequences are presented to each. At any stage the set of messages in *Any*'s bucket is a subset of those in *Eager*'s bucket, with any differences arising from steps when there is exactly one arrival, there are no sends from the bucket, and *Eager* sends but *Any* is silent. We may further couple the behavior of the common subset of messages.

Let  $\lambda = \lambda_2 \approx 0.659$  be the (unique) root of  $\lambda = 1 - \lambda e^{-\lambda}$ .

LEMMA 19. *For the coupled genies Any and Eager defined above, if  $\text{Out}_A$  and  $\text{Out}_E$  are the corresponding output functions, we define*

$$\Delta\text{Out}(t) = \text{Out}_E(t) - \text{Out}_A(t).$$

For any  $\lambda \leq \lambda_2$  and any  $\epsilon > 0$ ,

$$\text{Prob}[\Delta\text{Out}(t) \geq -\epsilon t \text{ for all } t \geq T] \rightarrow 1 \text{ as } T \rightarrow \infty.$$

*Proof.* Let  $c_0$  be the indicator for the event that no common messages are sent. Let  $c_1$  be the indicator for the event that exactly one common message is sent. Let  $c_*$  be the indicator for the event that more than one common message is sent. In addition, for the messages which are only in *Eager*'s bucket, we use the similar indicators  $e_0, e_1, e_*$ . Let  $a_0, a_1$  represent *Any* not sending, or sending, *additional* messages, respectively. (Note that *Eager*'s behavior is fully determined since it will always send exactly one additional message if none of the messages in its bucket send. Otherwise, it will send no additional messages.)

We write  $Z(t)$  for  $\Delta\text{Out}(t) - \Delta\text{Out}(t-1)$ , for  $t > 0$ , so  $Z$  represents the difference in success between *Eager* and *Any* in one step. In terms of the indicators we have

$$\begin{aligned} Z(t) &= S_E(t) - S_A(t) \\ &= i_{0gE1}(t) + i_{1gE0}(t) - i_{0gA1}(t) - i_{1gA0}(t), \end{aligned}$$

where  $S_E(t)$  is the indicator random variable for a success of *Eager* at time  $t$  and  $gE1(t)$  is the event that *Eager* sends exactly one message during step  $t$  (and so on) as in the paragraph before Lemma 16. Thus,

$$Z(t) \geq i_{0c_0}(a_0(e_0 + e_1) - a_1e_*) - i_{0c_1}(e_1 + e_*) - i_{1c_0}a_0.$$

Note that if the number of arrivals plus the number of common bucket sends is more than 1, then neither genie can succeed. We also need to keep track of the number,  $\Delta B$ , of extra messages in *Eager*'s bucket. At any step, at most one new extra message can arrive; the indicator for this event is  $i_{1c_0}a_0$ , i.e., there is a single arrival and no sends from the common bucket, so if *Any* does not send, then this message succeeds but *Eager*'s send will cause a failure. The number of "extra" messages leaving *Eager*'s bucket at any step is unbounded, given by a random variable we could show as  $\mathbf{e} = 1 \cdot e_1 + 2 \cdot e_2 + \dots$ . However,  $\mathbf{e}$  dominates  $e_1 + e_*$  and it is sufficient to use the latter. The change at one step in the number of extra messages satisfies

$$\Delta B(t) - \Delta B(t-1) = i_{1c_0}a_0 - \mathbf{e} \leq i_{1c_0}a_0 - (e_1 + e_*).$$

Next we define  $Y(t) = Z(t) - \alpha(\Delta B(t) - \Delta B(t-1))$  for some positive constant  $\alpha$  to be chosen below. Note that  $X(t) = \sum_{j=1}^t Y(j) = \Delta \text{Out}(t) - \alpha \Delta B(t)$ . We also define

$$Y'(t) = i_0 c_0 (a_0 (e_0 + e_1) - a_1 e_*) - i_0 c_1 (e_1 + e_*) - i_1 c_0 a_0 - \alpha (i_1 c_0 a_0 - (e_1 + e_*))$$

and  $X'(t) = \sum_{j=1}^t Y'(j)$ . Note that  $Y(t) \geq Y'(t)$ . That is,  $Y(t)$  dominates  $Y'(t)$ .

We can identify five (exhaustive) cases A, B, C, D, E, depending on the values of the  $c$ 's,  $a$ 's, and  $e$ 's, such that in each case  $Y'(t)$  dominates a given random variable depending only on  $I(t)$ :

- A.  $c_*$ :  $Y'(t) \geq 0$ .
- B.  $(c_1 + c_0 a_1)(e_1 + e_*)$ :  $Y'(t) \geq \alpha - i_0$ .
- C.  $(c_1 + c_0 a_1)e_0$ :  $Y'(t) \geq 0$ .
- D.  $c_0 a_0 (e_0 + e_1)$ :  $Y'(t) \geq i_0 - (1 + \alpha)i_1$ .
- E.  $c_0 a_0 e_*$ :  $Y'(t) \geq \alpha - (1 + \alpha)i_1$ .

For example, the correct interpretation of case B is “conditioned on  $(c_1 + c_0 a_1)(e_1 + e_*) = 1$ , the value of  $Y'(t)$  is at least  $\alpha - i_0$ .” Since  $E[i_0] = e^{-\lambda}$  and  $E[i_1] = \lambda e^{-\lambda}$ , we have  $E[Y'(t)] \geq 0$  in each case, provided that  $\max\{e^{-\lambda}, \lambda e^{-\lambda}/(1 - \lambda e^{-\lambda})\} \leq \alpha \leq 1/\lambda - 1$ . There exists such an  $\alpha$  for any  $\lambda \leq \lambda_2$ ; for such  $\lambda$  we may take the value, say,  $\alpha = e^{-\lambda}$ .

Let  $\mathcal{F}_t$  be the  $\sigma$ -field generated by the first  $t$  steps of the coupled process. Let  $\hat{Y}(t) = Y'(t) - E[Y'(t) | \mathcal{F}_{t-1}]$  and let  $\hat{X}(t) = \sum_{i=1}^t \hat{Y}(i)$ . The sequence  $\hat{X}(0), \hat{X}(1), \dots$  forms a *martingale* (see Definition 4.11 of [21]) since  $E[\hat{X}(t) | \mathcal{F}_{t-1}] = \hat{X}(t-1)$ . Furthermore, there is a positive constant  $c$  such that  $|\hat{X}(t) - \hat{X}(t-1)| \leq c$ . Thus, we can apply the Hoeffding–Azuma inequality (see Theorem 4.16 of [21]).

**THEOREM 20** (Hoeffding–Azuma). *Let  $X_0, X_1, \dots$  be a martingale sequence such that for each  $k$*

$$|X_k - X_{k-1}| \leq c_k,$$

where  $c_k$  may depend upon  $k$ . Then, for all  $t \geq 0$  and any  $\lambda > 0$ ,

$$\text{Prob}[|X_t - X_0| \geq \lambda] \leq 2 \exp\left(-\frac{\lambda^2}{2 \sum_{k=1}^t c_k^2}\right).$$

In particular, we can conclude that

$$\text{Prob}[\hat{X}_t \leq -\epsilon t] \leq 2 \exp\left(-\frac{\epsilon^2 t}{2c^2}\right).$$

Our choice of  $\alpha$  above ensured that  $E[Y'(t) | \mathcal{F}_{t-1}] \geq 0$ . Hence  $Y'(t) \geq \hat{Y}(t)$  and  $X'(t) \geq \hat{X}(t)$ . We observed earlier that  $X(t) \geq X'(t)$ . Thus,  $X(t) \geq \hat{X}(t)$  so we have

$$\text{Prob}[X_t \leq -\epsilon t] \leq 2 \exp\left(-\frac{\epsilon^2 t}{2c^2}\right).$$

Since  $\sum_{t \geq 0} 2 \exp(-\frac{\epsilon^2 t}{2c^2})$  converges, we deduce that

$$\text{Prob}[X(t) \geq -\epsilon t \text{ for all } t \geq T] \rightarrow 1 \text{ as } T \rightarrow \infty.$$

Since  $\Delta \text{Out}(t) = X(t) + \alpha \Delta B(t) \geq X(t)$  for all  $t$ , we obtain the required conclusion.  $\square$

Finally, we can prove the main results of this section.

**THEOREM 21.** *Let  $P$  be an acknowledgment-based protocol. Let  $\lambda = \lambda_1 \approx 0.531$  be the (unique) root of  $\lambda = (1 + \lambda)e^{-2\lambda}$ . Then*

1.  $P$  is transient for arrival rates greater than  $\lambda_1$ ;
2.  $P$  has capacity no greater than  $\lambda_1$ .

*Proof.* Let  $\lambda$  be the arrival rate, and suppose  $\lambda > \lambda_1$ . If  $\lambda > \lambda_0 \approx 0.567$ , then the result follows from Lemma 16. Otherwise, we can assume that  $\lambda < \lambda_2 \approx 0.659$ . If  $E$  is the eager genie derived from  $P$ , then the corresponding Backlogs satisfy  $\text{Backlog}_P(t) = \text{Backlog}_E(t) + \Delta\text{Out}(t)$ . The results of Lemmas 18 and 19 show that, for some  $\varepsilon > 0$ , both  $\text{Prob}[\text{Backlog}_E(t) > 2\varepsilon t \text{ for all } t \geq T]$  and  $\text{Prob}[\Delta\text{Out}(t) \geq -\varepsilon t \text{ for all } t \geq T]$  tend to 1 as  $T \rightarrow \infty$ . The conclusion of the theorem follows.  $\square$

**Appendix. Proof of Lemma 11.** Let  $j(r, p) = -h(r, p)$ . We will show that for any  $r \in [0, 1]$  and  $p \in [0, 1]$ ,  $j(r, p) \leq -0.003$ .

*Case 1.*  $r + p - rp \geq r \geq B/A$  and  $p \geq r$ . In this case we have

$$\begin{aligned} g(r, p) &= e^{-\lambda}((1-r)p + (1-p)r + (1-p)(1-r)\lambda), \\ j(r, p) &= g(r, p) - \lambda. \end{aligned}$$

Observe that

$$j(r, p) = e^{-\lambda} \sum_{i=0}^1 \sum_{j=0}^1 c_{i,j} p^i r^j,$$

where the coefficients  $c_{i,j}$  are defined as follows:

$$\begin{aligned} c_{0,0} &= \lambda(1 - e^\lambda), \\ c_{1,0} &= 1 - \lambda, \\ c_{0,1} &= 1 - \lambda, \\ c_{1,1} &= -2 + \lambda. \end{aligned}$$

Note that the only positive coefficients are  $c_{1,0}$  and  $c_{0,1}$ . Thus, if  $p \in [p_1, p_2]$  and  $r \in [r_1, r_2]$ , then  $j(r, p)$  is at most  $\mathcal{U}(p_1, p_2, r_1, r_2)$ , which we define as

$$e^{-\lambda}(c_{0,0} + c_{1,0}p_2 + c_{0,1}r_2 + c_{1,1}p_1r_1).$$

Now we need only check that for all  $r_1 \in (B/A - 0.01, 1)$  and  $p_1 \in [r_1, 1]$  such that  $p_1$  and  $r_1$  are multiples of 0.01,  $\mathcal{U}(p_1, p_1 + 0.01, r_1, r_1 + 0.01)$  is at most  $-0.003$ . This is the case. (The highest value is  $\mathcal{U}(0.45, 0.46, 0.45, 0.46)$ , which is  $-0.00366228$ .)

*Case 2.*  $r + p - rp \geq r \geq B/A$  and  $p < r$ . Now we have

$$\begin{aligned} g(r, p) &= e^{-\lambda} \left( (1-r)p + (1-p) \frac{r - r^2/2}{1 - p/2} + (1-p)(1-r)\lambda \right), \\ j(r, p) &= g(r, p) - \lambda. \end{aligned}$$

Observe that

$$(1 - p/2)j(r, p) = e^{-\lambda} \sum_{i=0}^2 \sum_{j=0}^2 c_{i,j} p^i r^j,$$

where the coefficients  $c_{i,j}$  are defined as follows:

$$\begin{aligned} c_{0,0} &= \lambda(1 - e^\lambda), \\ c_{1,0} &= 1 - 3\lambda/2 + e^\lambda\lambda/2, \\ c_{0,1} &= 1 - \lambda, \\ c_{1,1} &= -2 + 3\lambda/2, \\ c_{2,0} &= -1/2 + \lambda/2, \\ c_{0,2} &= -1/2, \\ c_{2,1} &= 1/2 - \lambda/2, \\ c_{1,2} &= 1/2, \\ c_{2,2} &= 0. \end{aligned}$$

Note that the only positive coefficients are  $c_{1,0}$ ,  $c_{0,1}$ ,  $c_{2,1}$ , and  $c_{1,2}$ . Thus, if  $p \in [p_1, p_2]$  and  $r \in [r_1, r_2]$ , then  $j(r, p)$  is at most  $\mathcal{U}(p_1, p_2, r_1, r_2)$ , which we define as

$$\frac{c_{0,0} + c_{1,0}p_2 + c_{0,1}r_2 + c_{1,1}p_1r_1 + c_{2,0}p_1^2 + c_{0,2}r_1^2 + c_{2,1}p_2^2r_2 + c_{1,2}p_2r_2^2 + c_{2,2}p_1^2r_1^2}{e^\lambda(1 - p_2/2)}.$$

Now we need only check that for all  $r_1 \in (B/A - 0.005, 1)$  and  $p_1 \in [0, r_1]$  such that  $p_1$  and  $r_1$  are multiples of 0.005,  $\mathcal{U}(p_1, p_1 + 0.005, r_1, r_1 + 0.005)$  is at most  $-0.003$ . This is the case. (The highest value for these parameters is  $\mathcal{U}(0.45, 0.455, 0.455, 0.46) = -0.00479648$ .)

*Case 3.*  $r + p - rp \geq B/A \geq r$  and  $p \geq r$ . In this case we have

$$\begin{aligned} g(r, p) &= e^{-\lambda}((1-r)p + (1-p)r + (1-p)(1-r)\lambda), \\ j(r, p) &= g(r, p) - \lambda - (-Ar + B)e^{-\lambda}(1-r)p. \end{aligned}$$

Observe that

$$j(r, p) = e^{-\lambda} \sum_{i=0}^2 \sum_{j=0}^2 c_{i,j} p^i r^j,$$

where the coefficients  $c_{i,j}$  are defined as follows:

$$\begin{aligned} c_{0,0} &= \lambda(1 - e^\lambda), \\ c_{1,0} &= 1 - B - \lambda, \\ c_{0,1} &= 1 - \lambda, \\ c_{1,1} &= -2 + A + B + \lambda, \\ c_{2,0} &= 0, \\ c_{0,2} &= 0, \\ c_{2,1} &= 0, \\ c_{1,2} &= -A, \\ c_{2,2} &= 0. \end{aligned}$$

Note that the only positive coefficients are  $c_{1,0}$  and  $c_{0,1}$ . Thus, if  $p \in [p_1, p_2]$  and  $r \in [r_1, r_2]$ , then  $j(r, p)$  is at most  $\mathcal{U}(p_1, p_2, r_1, r_2)$ , which we define as

$$\frac{c_{0,0} + c_{1,0}p_2 + c_{0,1}r_2 + c_{1,1}p_1r_1 + c_{2,0}p_1^2 + c_{0,2}r_1^2 + c_{2,1}p_1^2r_1 + c_{1,2}p_1r_1^2 + c_{2,2}p_1^2r_1^2}{e^\lambda}.$$

Now we need only check that for all  $p_1 \in [0, 1)$  and  $r_1 \in [0, p_1]$  such that  $p_1$  and  $r_1$  are multiples of 0.01,  $\mathcal{U}(p_1, p_1 + 0.01, r_1, r_1 + 0.01)$  is at most  $-0.003$ . This is the case. (The highest value is  $\mathcal{U}(0.44, 0.45, 0.44, 0.45) = -0.00700507$ .)

*Case 4.*  $r + p - rp \geq B/A \geq r$  and  $p < r$ . Now we have

$$g(r, p) = e^{-\lambda} \left( (1-r)p + (1-p) \frac{r - r^2/2}{1 - p/2} + (1-p)(1-r)\lambda \right),$$

$$j(r, p) = g(r, p) - \lambda - (-Ar + B)e^{-\lambda}(1-r)p.$$

Observe that

$$j(r, p) = e^{-\lambda}(1/2) \frac{\sum_{i=0}^2 \sum_{j=0}^2 c_{i,j} p^i r^j}{1 - p/2},$$

where the coefficients  $c_{i,j}$  are defined as follows:

$$\begin{aligned} c_{0,0} &= 2\lambda(1 - e^\lambda), \\ c_{1,0} &= 2 - 2B - 3\lambda + \lambda e^\lambda, \\ c_{0,1} &= 2 - 2\lambda, \\ c_{1,1} &= -4 + 2A + 2B + 3\lambda, \\ c_{2,0} &= -1 + B + \lambda, \\ c_{0,2} &= -1, \\ c_{2,1} &= 1 - A - B - \lambda, \\ c_{1,2} &= 1 - 2A, \\ c_{2,2} &= A. \end{aligned}$$

Note that the coefficients are all negative except  $c_{1,0}$ ,  $c_{0,1}$ , and  $c_{2,2}$ . Thus, if  $p \in [p_1, p_2]$  and  $r \in [r_1, r_2]$ , then  $j(r, p)$  is at most  $\mathcal{U}(p_1, p_2, r_1, r_2)$ , which we define as

$$\frac{c_{0,0} + c_{1,0}p_2 + c_{0,1}r_2 + c_{1,1}p_1r_1 + c_{2,0}p_1^2 + c_{0,2}r_1^2 + c_{2,1}p_1^2r_1 + c_{1,2}p_1r_1^2 + c_{2,2}p_2^2r_2^2}{2e^\lambda(1 - p_2/2)}.$$

Now we need only check that for all  $p_1 \in [0, 1)$  and  $r_1 \in [p_1, 1)$  such that  $p_1$  and  $r_1$  are multiples of 0.01,  $\mathcal{U}(p_1, p_1 + 0.01, r_1, r_1 + 0.01)$  is at most  $-0.003$ . This is the case. (The highest value is  $\mathcal{U}(0.44, 0.45, 0.44, 0.45) = -0.00337716$ .)

*Case 5.*  $B/A \geq r + p - rp \geq r$  and  $p \geq r$ . In this case we have

$$\begin{aligned} g(r, p) &= e^{-\lambda}((1-r)p + (1-p)r + (1-p)(1-r)\lambda), \\ j(r, p) &= g(r, p) - \lambda \\ &\quad + (-A(r + p - rp) + B)(1 - (1-r)(1-p)e^{-\lambda}(1 + \lambda)) \\ &\quad - (-Ar + B)e^{-\lambda}(1-r)p. \end{aligned}$$

Observe that

$$j(r, p) = e^{-\lambda} \sum_{i=0}^2 \sum_{j=0}^2 c_{i,j} p^i r^j,$$

where the coefficients  $c_{i,j}$  are defined as follows:

$$\begin{aligned} c_{0,0} &= -B + Be^\lambda + \lambda - B\lambda - e^\lambda\lambda, \\ c_{1,0} &= 1 + A - Ae^\lambda - \lambda + A\lambda + B\lambda, \\ c_{0,1} &= 1 + A + B - Ae^\lambda - \lambda + A\lambda + B\lambda, \\ c_{1,1} &= -2 - 2A + Ae^\lambda + \lambda - 3A\lambda - B\lambda, \\ c_{2,0} &= -A - A\lambda, \\ c_{0,2} &= -A - A\lambda, \\ c_{2,1} &= 2A + 2A\lambda, \\ c_{1,2} &= A + 2A\lambda, \\ c_{2,2} &= -A - A\lambda. \end{aligned}$$

Note that the only positive coefficients are  $c_{1,0}$ ,  $c_{0,1}$ ,  $c_{2,1}$ , and  $c_{1,2}$ . Thus, if  $p \in [p_1, p_2]$  and  $r \in [r_1, r_2]$ , then  $j(r, p)$  is at most  $\mathcal{U}(p_1, p_2, r_1, r_2)$ , which we define as

$$\frac{c_{0,0} + c_{1,0}p_2 + c_{0,1}r_2 + c_{1,1}p_1r_1 + c_{2,0}p_1^2 + c_{0,2}r_1^2 + c_{2,1}p_2^2r_2 + c_{1,2}p_2r_2^2 + c_{2,2}p_1^2r_1^2}{e^\lambda}.$$

Now we need only check that for all  $p_1 \in [0, 1)$  and  $r_1 \in [0, p_1]$  such that  $p_1$  and  $r_1$  are multiples of 0.01,  $\mathcal{U}(p_1, p_1 + 0.01, r_1, r_1 + 0.01)$  is at most  $-0.003$ . This is the case. (The highest value is  $\mathcal{U}(0.19, 0.2, 0.19, 0.2) = -0.0073656$ .)

*Case 6.*  $B/A \geq r + p - rp \geq r$  and  $p < r$ . Now we have

$$\begin{aligned} g(r, p) &= e^{-\lambda} \left( (1-r)p + (1-p) \frac{r-r^2/2}{1-p/2} + (1-p)(1-r)\lambda \right), \\ j(r, p) &= g(r, p) - \lambda \\ &\quad + (-A(r+p-rp) + B)(1 - (1-r)(1-p)e^{-\lambda}(1+\lambda)) \\ &\quad - (-Ar + B)e^{-\lambda}(1-r)p. \end{aligned}$$

Observe that

$$(1-p/2)j(r, p) = e^{-\lambda} \sum_{i=0}^3 \sum_{j=0}^2 c_{i,j} p^i r^j,$$

where the coefficients  $c_{i,j}$  are defined as follows:

$$\begin{aligned} c_{0,0} &= -B + Be^\lambda + \lambda - B\lambda - e^\lambda\lambda, \\ c_{1,0} &= 1 + A + B/2 - Ae^\lambda - Be^\lambda/2 - 3\lambda/2 + A\lambda + 3B\lambda/2 + e^\lambda\lambda/2, \\ c_{0,1} &= 1 + A + B - Ae^\lambda - \lambda + A\lambda + B\lambda, \\ c_{1,1} &= -2 - 5A/2 - B/2 + 3Ae^\lambda/2 + 3\lambda/2 - 7A\lambda/2 - 3B\lambda/2, \\ c_{2,0} &= -1/2 - 3A/2 + Ae^\lambda/2 + \lambda/2 - 3A\lambda/2 - B\lambda/2, \\ c_{0,2} &= -1/2 - A - A\lambda, \\ c_{2,1} &= 1/2 + 3A - Ae^\lambda/2 - \lambda/2 + 7A\lambda/2 + B\lambda/2, \\ c_{1,2} &= 1/2 + 3A/2 + 5A\lambda/2, \\ c_{2,2} &= -3A/2 - 2A\lambda, \\ c_{3,0} &= A/2 + A\lambda/2, \\ c_{3,1} &= -A - A\lambda, \\ c_{3,2} &= A/2 + A\lambda/2. \end{aligned}$$

Note that the only positive coefficients are  $c_{1,0}$ ,  $c_{0,1}$ ,  $c_{2,1}$ ,  $c_{1,2}$ ,  $c_{3,0}$ , and  $c_{3,2}$ . Thus, if  $p \in [p_1, p_2]$  and  $r \in [r_1, r_2]$ , then  $j(r, p)$  is at most  $\mathcal{U}(p_1, p_2, r_1, r_2)$ , which we define as

$$c_{0,0} + c_{1,0}p_2 + c_{0,1}r_2 + c_{1,1}p_1r_1 + c_{2,0}p_1^2 + c_{0,2}r_1^2 + c_{2,1}p_2^2r_2 + c_{1,2}p_2r_2^2 \\ + c_{2,2}p_1^2r_1^2 + c_{3,0}p_2^3 + c_{3,1}p_1^3r_1 + c_{3,2}p_2^3r_2^2$$

divided by  $e^\lambda(1 - p_2/2)$ .

Now we need only check that for all  $p_1 \in [0, 1)$  and  $r_1 \in [p_1, 1)$  such that  $p_1$  and  $r_1$  are multiples of 0.005,  $\mathcal{U}(p_1, p_1 + 0.005, r_1, r_1 + 0.005)$  is at most  $-0.003$ . This is the case. (The highest value is  $\mathcal{U}(0.01, 0.015, 0.3, 0.305) = -0.00383814$ .)

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