Carnegie Mellon University Research Showcase @ CMU

Department of Engineering and Public Policy

Carnegie Institute of Technology

3-2000

Dynamic Pricing as Congestion Control in ATM **Nétworks**

Jon M. Peha Carnegie Mellon University, peha@andrew.cmu.edu

Follow this and additional works at: http://repository.cmu.edu/epp



Part of the Engineering Commons

Published In

Computer Networks, 32, 3, 333-345.

This Article is brought to you for free and open access by the Carnegie Institute of Technology at Research Showcase @ CMU. It has been accepted for inclusion in Department of Engineering and Public Policy by an authorized administrator of Research Showcase @ CMU. For more information, please contact research-showcase@andrew.cmu.edu.

To appear in Computer Networks

Dynamic Pricing and Congestion Control for Best-Effort ATM Services¹

Jon M. Peha

Carnegie Mellon University, Dept. of ECE, Pittsburgh, PA 15213-3890 Phone: (412) 268-7126, Fax: (412) 268-2860, peha@ece.cmu.edu http://www.ece.cmu.edu/~peha

Abstract

Several researchers have recently advocated dynamic pricing mechanisms such as the *smart market*. This paper explores how dynamic state-dependent pricing and explicit congestion control can both be used to avoid and alleviate congestion. Dynamic pricing has significant advantages for heterogeneous traffic, although this paper demonstrates that this approach reduces raw throughput somewhat. It is shown that when propagation delay is non-trivial, as is the case in wide-area networks, a *slow-reacting* version of dynamic pricing is preferable. This paper also advocates use of novel *stream-oriented* best-effort ATM services, with which a stream's arrival process is declared to the network before transmission begins and then policed, although there are no performance guarantees and none of these best-effort streams are ever blocked. With this approach, it is possible to provide price incentives for applications to decrease traffic burstiness, and to reveal important information about their packet streams, making mechanisms like slow-reacting dynamic pricing more practical.

Key-words: ATM, Best Effort Traffic, Congestion Control, Integrated Services Networks, Pricing, Smart Market.

1 Introduction

In the coming years, many telephone networks, cable TV networks, and computer networks like the Internet will become *integrated-services networks*, which are networks that offer multiple services to support diverse traffic, e.g. one service for telephony, and another for pay-per-view VCR-quality movies. Each service can have a different price. This paper will address usage-based pricing mechanisms, where price varies according to how a customer uses the network, e.g. how many packets are sent, when they are sent, etc. Non-usage-based network revenue sources such as flat monthly fees or government subsidies may also be significant, but are outside the scope of this paper.

Some of the goals for usage-based pricing schemes are the same as those for important traffic control algorithms. First, pricing is a mechanism for resource allocation. Instead of explicitly assigning resources to specific packet streams, pricing signals to users that those who derive a value for a given service that is below its current price should not use the service, thereby allocating resources to the more valuable streams. Second, pricing is used as an incentive to adjust user behavior, which is an alternative to placing specific constraints on user behavior. Usage-based prices can induce users to change factors like transmission rate, burstiness, or the time of day of their transmission. It can also induce users to reveal information about the traffic they are sending,

¹This material is based upon work supported in part by Lucent Technologies and by AT&T.

like the packet arrival process [1], a stream's value to the user [2], or its performance requirements. Indeed, without price incentives, users would never reveal to the network that a given stream could tolerate significant delays or losses, making it impossible to use traffic control approaches like [3, 4, 5, 6, 7], which allow the network to improve performance and carry significantly greater traffic loads [8]. Thus, it is possible that the network service provider and all users will benefit from usage-based pricing [9, 10, 11, 12], assuming that the costs of monitoring and billing are not significant [13]. Note that these benefits can be realized even if there is no actual exchange of money. For example, an enterprise or military network can allocate resources and provide incentives by distributing abstract units of credit, which are redeemable for network services. It is also possible that some will benefit and some will be harmed by usage-based pricing [14], but the overall impact should be positive.

This paper will examine usage-based pricing and traffic control mechanisms working in concert, focusing on connection-oriented networks using rate-based flow control, as is the case in many asynchronous transfer mode (ATM) networks. This paper will show that pricing mechanisms can motivate a network designer to modify, supplement, or even replace some traffic control mechanisms such as reactive congestion control and admission control. One particular issue we will address is whether price should vary dynamically (or "responsively" [11]) to follow changes in network state (and not just time-of-day) as a number of researchers have proposed, just as traffic control algorithms might dynamically vary the bounds on the rate that packets are allowed to enter the network. Such a pricing mechanism may convince users not to transmit when the network is becoming congested, thereby avoiding or alleviating the effects of congestion. Dynamic statedependent pricing will appear to users as prices that fluctuate randomly, which is not generally a desirable property. Indeed, it is pointless in applications where humans rather than computers directly determine when transmissions are made. It is hard to imagine a person watching longdistance prices fluctuate wildly on a meter, waiting for the perfect moment to make a telephone call. However, there are applications where dynamic state-dependent pricing makes more sense. For example, a user wandering the World Wide Web (WWW) might instruct her browser to suspend operation, to retrieve text but not images, or to simply decrease the data rate, when prices are high. Similarly, a videoconference application may automatically allow video resolution to degrade or switch from color to black and white when prices are high [15]. If prices should vary with network state, how quickly? If you are watching a video changing back and forth between color and black-and-white, you would prefer price to change slowly, but if pricing is a form of congestion control, it would be better if prices could change rapidly. Other factors are also important. In particular, we will consider the impact of propagation delay across the network on the utility of dynamic state-dependent pricing.

Another issue to be addressed is whether the price for transmitting an individual packet should be independent of the other packets in the packet stream, or whether the entire stream should somehow be considered when setting the price. This is somewhat analogous to the debate about whether or not traffic control algorithms should view each packet as an independent entity, as is the case in a datagram protocol like the Internet's IP. We will argue that ATM pricing should be based in part on the stream's arrival process even in some cases where the packet stream is sent best effort, i.e. without specific guarantees about delay performance.

The next section will describe different approaches to pricing. This will allow us to describe the issues addressed in this paper in more detail. The model of network and user behavior that we use to study these issues will be presented in Section 3, and the results achieved with different pricing and congestion control mechanisms is in Section 4. Section 5 presents the resulting conclusions.

2 Taxonomy and Issues

This section will further define the pricing issues to be addressed in this paper. A wide variety of pricing mechanisms have been proposed [16]. We begin by proposing a taxonomy that describes ways that packet streams might be admitted to the network, and corresponding pricing mechanisms: guaranteed, packet-oriented best effort, and stream-oriented best effort. Each of these three approaches may be appropriate for some types of traffic.

With some applications like telephony, it is preferable for a packet stream to be blocked than for it to be admitted and then experience unacceptable performance. Such traffic requires an a priori guarantee that performance requirements will be met. The quaranteed services meet this need by requiring calls to go through an admission control process before transmissions can begin. The application must first state the stream's packet arrival process (average data rate, peak data rate, average burst length, etc.) and its performance requirements. In a connection-oriented network, this information can be used to determine the load on every link in the network. In datagram networks, routing issues must also be considered, which can make this more difficult. If it is determined that the requirements of this new stream and all existing streams cannot be met, then the call must be blocked. Obviously, it is never possible to make performance guarantees unless the application declares its arrival process in advance, and that description is sufficiently accurate. Consequently, if the stream is admitted, a policing mechanism must insure that the data rate and burstiness of the actual packet arrival process is no greater than that of the stated arrival process. (An alternative way to offer a guaranteed service would be to rent access to network resources and let the application decide what it needs to meet its requirements [17]. This greatly simplifies the network's problem, but requires the user to know more about the network architecture, and makes resource sharing much more difficult.)

When resources are finite, prices should depend in part on the amount of resources consumed by each packet stream, and this is a function of the stream's average data rate, burstiness, performance objectives, and the blocking probability that is tolerable [18, 19, 20]. We have proposed a framework in which the price of each service depends on all of these factors [20], and devised a method of determining optimal prices and optimal capacity [20]. Price for a guaranteed service in this framework also depends on time-of-day, and therefore expected network load, but not on actual load or network state. Once a guaranteed stream is admitted, the network is not able to reclaim the allocated resources, or change the price, until the application decides to terminate the call. Consequently, network state at the instant the call is admitted is far less important than expected load over the duration of the call. However, this argument holds only when performance and price guarantees are made.

The alternative to a guaranteed service is a best effort service, in which no a priori performance guarantee is asked for or given. We divide best effort services into two categories: packet-oriented and stream-oriented. Beginning with the former, each packet is handled independently. The network traffic control mechanisms therefore have no idea what the packet arrival process is for a given stream, because they are not aware of packet streams. The price for a packet also does not depend on the characteristics of other packets in the stream. One serious inherent limitation of this approach is that there is no price disincentive for highly bursty streams, so traffic is likely to be burstier, reducing throughput. The only other option is to force all bursty streams to be close to constant-bit-rate, greatly increasing their delay, even if the user would happily pay for better service. This alone may be a reason to discourage use of the packet-oriented best effort approach by pricing it high.

The simplest pricing mechanism of this kind is a fixed cost per packet or per bit. However, demand fluctuates randomly. During periods where demand is low, few users may be willing to pay this price, and the network will be underutilized. When demand is high, the network can be oversubscribed, possibly leading to congestion. This can be solved with a smart market mechanism [2], in which the user specifies the value of each packet², and the current spot price for transmitting across a given link is set such that the available capacity is just enough for all packets whose value exceeds that price. This is an effective way to price best-effort services in a single-link network in which the queueing delay of the best-effort packets that are transmitted is unimportant to users [2, 11, 20]. However, there are a number of additional issues to be considered in a network of queues. This paper will focus on one such issue, with others to be left for future work: unless propagation delay is negligible, as in a local-area network, it is not possible to determine the state of every link in a network, calculate the appropriate prices, and advertise these prices throughout the network, before the state information becomes outdated. A distributed approach to pricing is needed, and traffic sources will inevitably decide whether or not to transmit based on slightly outdated information on the state of the network. Note that this limitation is no different from the problems of reactive congestion control mechanisms, where sources inject packets into the network based on somewhat outdated information on the presence or absence of congestion.

Finally, we consider stream-oriented best-effort. As with guaranteed streams, applications must first declare their packet arrival process to the network, which is the most significant difference between a packet-oriented and stream-oriented service. Policing mechanisms will later penalize the stream if this declaration is not accurate. This can be done in a variety of ways. A strict policing mechanism can delay or discard packets to insure that the stated arrival process parameters are exactly adhered to, so loads are well known. An alternative is to decrease the priority of packets from a source that is transmitting faster than it is supposed to, as in [3]. This way, the packets are sent when there is nothing else waiting, but the offending stream cannot degrade performance for other streams. In a third approach, the policing mechanism simply marks excess packets as discard eligible. This approach is used in frame relay, and has great potential for connectionless networks like the Internet [21, 22]. Applications may also declare performance objectives as well as the arrival process. The network can then attempt to meet (and not greatly exceed) those objectives as in [3, 4, 5, 6, 7], thereby allowing the network to improve performance and carry more traffic, but there is no firm guarantee that the objectives will actually be met. Alternatively, performance objectives could be replaced with priorities [9, 12], which is simpler to implement but is less effective at meeting real objectives [8], and it can be difficult to determine which priority an application should choose to meet its objectives. As with packet-oriented best effort, no stream-oriented best-effort calls are ever blocked.

There are two important advantages to stream-oriented best effort. One is that prices can reflect the stated burstiness of streams, so it is possible to provide disincentives for highly bursty traffic. The charge to a user could be a function of how long the stream was set up and/or how many packets were sent, and both of these prices can depend on the stated burstiness of the stream. The other advantage is that the network is given more information about the rate at which packets will be arriving. If policing mechanisms insure that the stated arrival process parameters are adhered to, a connection-oriented network such as an ATM network can then determine the load on all of its links, and use this information to improve service. Since revealing this information improves network efficiency, the application should again be rewarded with lower prices. Thus, the cost of transmitting a given stream via stream-oriented best effort should be less than transmitting the

²In a connection-oriented network like an ATM network, this value may be implicit in the virtual path or virtual circuit identifier. In a datagram network, room must be made in the packet header, which is far less attractive.

same stream via packet-oriented best effort.

In this paper, we will evaluate the effectiveness of dynamic state-dependent pricing mechanisms as methods of allocating resources to the most valuable streams, and as methods of reacting to congestion. In the process, we will observe how these pricing mechanisms work in combination with and instead of traditional reactive congestion control mechanisms, i.e. mechanisms that treat all streams the same. We will determine whether these dynamic pricing approaches are effective in the face of significant propagation delay between the traffic sources and a congested link. To simplify the problem, however, we will assume that there is at most one potentially congested link through which any given stream will pass; this assumption will be relaxed in future work. We will also assume here that all sources are roughly the same distance from the congestion. The effectiveness of state-dependent pricing obviously depends on how much state information is known. We will also show how useful the information provided to the network with stream-oriented best effort traffic can be.

3 The Model

At a given time, there are N best-effort packet streams running through the potentially congested link. Routing is not affected by transient congestion. This is appropriate for all ATM networks, since they employ virtual channels and paths, and some datagram networks. Each of the N sources will choose to transmit when and only when the value to the user of packets in that stream exceeds the current price. Otherwise, the service is deemed too expensive to use. All N streams have the same arrival process, and all packets in a given stream are equally valuable, but no two streams have the exact same value per packet to their users. Thus, it is always possible to set price such that i streams have value greater than current price for any $i \leq N$. (If applications decrease transmission rate rather than suspending transmission when the price is high [11], this is equivalent to having multiple streams rather than one: e.g. a video stream is hierarchically encoded where the more important packets constitute a guaranteed stream and the less important packets are best effort with value 10 per packet. When price exceeds 10, the video switches to low data rate.)

We do not to presume to know the actual distribution of value in typical networks, and it can differ from network to network. Consequently, we will consider several distributions for value. Without loss of generality, we number the streams in increasing order of value. In each case, the value V_i for stream $i: 1 \le i \le N$ is proportional to i^a , and we will consider scenarios where a = 0, .5, 1, and 2. The exact values are scaled such that the average value $\sum_{i=1}^{N} V_i/N$ across all classes is 1. (In the case where a = 0, even though no two prices are allowed to be exactly equal, the differences are considered negligible.)

Each of the N streams alternates between on- and off-states. While on, they transmit at a constant rate, and while off, they do not transmit. There is a maximum rate at which a source can transmit; this is the rate at which they would prefer to transmit in the absence of congestion control. The durations of on-periods and off-periods are independent and exponentially distributed. Moreover, these durations are not affected by pricing or congestion control mechanisms, although the amount of information that can be transmitted during an on-period is. This would be a reasonable approximation for a variety of applications. For example, a web browsing application may stop transferring images or decrease their resolution when the network is congested (where each page retrieved from a proxy server may constitute an on-period). A processor in a distributed computation may actually produce fewer packets when network congestion limits the traffic it can exchange with peers. A video or voice application may send fewer of those packets for which

resources have not been guaranteed, thereby decreasing resolution, when the network is congested.

The propagation delay between each data source and the potentially congested link is P in each direction. At this link is an intelligent agent capable of sending congestion control or pricing messages back to the sources. When sending these messages, the goal is to maximize the total value derived from the network. The value derived from a given packet stream is the product of the value per packet to the user and the throughput of that stream. The total value derived from the network is the sum of the values derived from all streams. Note that total value does not depend on the actual revenue transferred from consumers to the network in the form of usage-based fees. This total value is equivalent to the economic social welfare, which regulators are typically expected to maximize in regulated industries, and it is generally what should be maximized in networks where pricing is strictly for resource allocation rather than the transfer of real currency, as in some enterprise or military networks. Total value is also a useful metric for unregulated profit-seeking companies; when more value is derived, consumers are willing to pay more through some combination of usage-based and non-usage-based fees. Consequently, more revenue can be collected [9, 23], although when there is competition, the actual dynamics can be quite complex. This is apparent in [18], which shows the amount of traffic of each type that would be carried and the prices set when two profit-seeking integrated-services carriers compete.

Value depends on throughput, and the problem of maximizing throughput is relatively simple unless the network is subject to the phenomenon of congestion, as most real networks are. When there is the potential for congestion, as load increases, so does inefficiency, so load eventually reaches a point at which throughput peaks and then declines. We will use the following model for congestion. When load is below a certain threshold, throughput through the link equals the arrival rate. Any time instantaneous load exceeds that threshold, instantaneous throughput decreases linearly from the maximum with slope -m. For example, consider a 150 Mb/s link that becomes congested when load hits .8. j sources are each transmitting at rate R. When $jR \leq .8 \cdot 150 = 120$ Mb/s, then throughput is jR. However, when jR > 120 Mb/s, then throughput is 120 - m(jR - 120), evenly split among the j sources. This is obviously an approximation, but is a reasonable representation of any congestion-prone network, and it has been shown to be an excellent description of the relationship between load and steady-state throughput in some links where congestion occurs because the loss of a single packet can require the retransmission of several packets [24]. In particular, in [24], each packet consists of 10 cells, and the loss of one or more cells in a packet due to buffer overflow means that the entire packet must be retransmitted, as can occur in ATM networks [25].

When too many best-effort streams are in the on-state, the link is congested, and throughput is suboptimal. So is the total value derived from the network. When a stream is best effort, there is no guarantee that performance, data rate, or price, will not change. Thus, when congestion occurs, this agent at the congested link can use a congestion control mechanism that limits the transmission rate of all best-effort streams. Then, instead of transmitting at the maximum allowable rate, each source that is currently in the on-state will transmit at the rate specified by this network agent, as can occur in the ATM Available Bit Rate (ABR) service. Another approach is to dynamically change prices. When this occurs, all best-effort streams for which the new price exceeds the value of the information will stop transmitting, and the others will continue to transmit at the maximum rate. It is also possible to use a combination of these mechanisms, where all streams whose value exceeds the current price will transmit at the rate set by the congestion control mechanism.

We consider three different congestion control mechanisms and three different pricing mechanisms, yielding a total of nine different approaches. The three congestion control mechanisms are signified by NC, SC, and FC. NC means that there is no congestion control, so sources always

transmit at the maximum rate. SC means there is a slow-reacting congestion control mechanism, so the network may impose a maximum transmission rate on every source that is a function of the total number of streams currently passing through the link, and this maximum rate will change whenever a new call is initiated or an old one is terminated. However, the maximum rate does not change as streams move between the on- and off-states. This rate is selected to maximize the total value derived by the system. Of course, the SC approach would be very difficult to implement without stream-oriented best-effort, because the network would not know the number N of streams with packet-oriented best effort. Instead, it would have to record the ever-changing packet arrival rates and do some kind of filtering to estimate the load. It would attempt to react quickly enough to notice when calls begin or end, but slowly enough not to react to temporary changes in packet arrival rate. This is far more complex and less accurate than what is possible with stream-oriented best effort, and it would lead to less stable prices and data rates.

Finally, FC means fast-reacting congestion control. In this case, the agent at the potentially congested link sends a message to all sources whenever the arrival rate to the congested link changes. This message indicates the maximum rate at which each source is allowed to transmit. Of course it takes one propagation delay for the message to reach the sources, and another delay P before it affects the traffic arrival rate at the congested link. In this period of $2 \cdot P$, some of the N streams might have gone from the on-state to the off-state, and vise versa. Thus, an FC mechanism at time t sets the maximum rate to maximize the expected total value derived from the system at time t + 2P, given the number of streams in the on-state at time t, the total number of streams N, and knowledge of the mean on- and off-periods. This knowledge is easily available with stream-oriented services, since it is declared, but it is more difficult to obtain with packet-oriented best effort, where it must be based on long-term statistics. (This maximum rate determination is a fairly simple calculation, and can be implemented with a look-up table.) FC is representative of current congestion control algorithms like ATM ABR which do not discriminate among active streams.

The three pricing policies (NP, SP, FP) are analogous to the three congestion control policies (NC, SC, FC). With NP, there is no usage-based pricing, so all sources transmit when in the onstate. SP means price is a function of the number of streams N, and does not change as streams alternate between the on- and off-states. SP is far more practical with stream-oriented best effort, since the number of packet streams is known with stream-oriented, and is difficult to determine with packet-oriented. (This is the principal difference between stream- and packet-oriented in this particular scenario, although other differences are possible.) FP means that prices change as instantaneous arrival rate changes. FP is a bit more complex than the comparable congestion control approach - FC. With NP or SP, an FC congestion control mechanism can easily determine the number of streams in the on-state. However, with FP, the pricing mechanism knows that a given stream is currently in the on-state if and only if the value per packet of that stream is greater than the current price. Otherwise, the source would not be transmitting any way. At best, the network can know whether the stream was in the on-state at the last time when price dipped sufficiently low for this source to transmit. As a result, our FP algorithm maintains a certain amount of historical information. In particular, at time t, it is assumed that the intelligent agent knows which sources were active at times t - iP for any positive integer i. The optimal price also depends on which of the N streams are in the on-state, rather than just how many of them are. This makes our FP algorithm somewhat complicated; in reality, a less complicated and less effective version might be implemented.

In scenarios where both the congestion control and pricing mechanisms are non-trivial (i.e. not NC or NP), prices and maximum transmission rates are selected together to maximize expected

total system value. Thus, FC-FP is clearly the best approach, and NC-NP is clearly the worst, but how significant are the differences, and what are the tradeoffs among the remaining approaches? In the next section, we will describe results achieved with this model.

4 Performance Results

In this section, we will address the issues raised in Section 2 using the model defined in Section 3. We can see the value of dynamic state-dependent pricing by observing the performance of systems using fast-reacting or slow-reacting pricing (FP or SP), as opposed to the case where there is no usage-based pricing (NP). Also, if SP or SC look promising, it is another argument for stream-oriented best effort, which makes it easy for the network to know how many best-effort packet streams are passing through a given link and their arrival processes. For the sake of comparison, FC-NP is most representative of current networks (e.g. ATM ABR).

The results shown in this section with fast-reacting pricing (FP) were achieved via simulation, and the 95% confidence interval is, at worst, within 5% of the values shown. For the other approaches, results were achieved analytically, so the results are exact.

We first consider the case where all N streams have roughly the same value (i.e., $V_i \propto i^0$). Figure 1 shows total value, which in this case equals total system throughput, as a function of N. The channel is 150 Mb/s, and throughput is maximized when the arrival rate is 120 Mb/s. When arrival rate exceeds 120 Mb/s, throughput is degraded at slope m=1. The average duration of an on-period is 100 ms, and the average duration of an off-period is 200 ms. (These could be reasonable values for streams that improve resolution of an associated variable-bit-rate video stream; other values will be considered later.) The maximum rate for a single source is 10 Mb/s. If there is no congestion control or dynamic pricing (NC-NP), then the congestion phenomenon is strong; value increases for small N but decreases for large N, eventually approaching 0. However, if there is dynamic pricing or dynamic congestion control or both, even if it is slow-reacting, value is not degraded as N grows large. Thus, dynamic state-dependent pricing could conceivably replace congestion control. However, the figure also shows that fast-reacting congestion control (FC) is somewhat more effective than dynamic pricing, since FC-NP always outperforms SC-FP. This is always the case when the objective is to maximize throughput (i.e. $V_i \propto i^0$). This can be explained as follows. A congestion control approach instructs all N streams to transmit at a given rate if they are in the on-state. There is uncertainty because the exact number of sources that will be in the on-state 2P from now is not known exactly, and if it is either too high or too low, throughput is degraded. A pricing approach would instead encourage the i "most valuable" streams to transmit at full rate if they are in the on-state. Since N > i, there is less variance in arrival rate with congestion control than with pricing, so expected throughput is slightly greater with congestion control.

We now consider a case where the value V_i of stream i is proportional to i (i.e., $V_i \propto i^1$), so there is more reason to use pricing. Figure 2 shows the throughput achieved by each of 45 streams with the various algorithms. The parameters are the same as in Figure 1, but with N=45. (The parameters in this curve will serve as our default assumptions in the rest of this section, so we need only specify which parameters differ from these.) When there is no pricing (NP), all streams have the same throughput, and that throughput is best with fast-reacting congestion control (FC) and worst with no congestion control (NC). With slow-reacting pricing (SP), throughput is close to the maximum for those willing to pay the price to transmit and 0 for the rest. However, with fast-reacting pricing (FP), many streams get throughputs between 0 and 10, because they are able

to transmit when and only when many of the more valuable streams are in the off-state. We also show an optimal curve, which is achievable only if the agent at the congested link can predict the future perfectly, or equivalently, if the propagation delay is 0. Its shape is similar to the FP curve.

Figures 3 and 4 show the total value derived by the network as a function of the number of streams N when streams may not have the same value. Results are shown for $V_i \propto i^0$, i^5 , i^1 , and i^2 . In Figure 3, the propagation delay P=1 ms, and in Figure 4, propagation delay is P=10 ms. From both figures, it is clear that dynamic pricing (FP or SP) is far more effective than NP when streams are not all equally valuable (i.e. a>0), as one would expect, and the more the value of the various streams can differ, the more useful dynamic pricing is. We also see in Figure 3 that FC-FP outperforms FC-SP in each scenario where pricing helps. In Figure 4, while FC-FP is still better than FC-SP, the difference is much smaller. Moreover, the implementation of a pricing mechanism that requires prices to be constantly recalculated would be much more complicated than a pricing mechanism in which prices are only calculated when a new stream begins or an old one terminates. All else being equal, users would also prefer a system in which price changed more slowly. If performance is comparable, as it appears in Figure 4, there may be an opportunity to use the simpler scheme.

Since propagation delay is clearly an important factor in the relative effectiveness of these schemes, Figure 5 shows total value as a function of propagation delay with our default parameters. FC-FP is a somewhat useful approach (relative to FC-SP) when propagation delay is 5 ms or less, but with a propagation delay greater than 10 ms, it only slightly outperforms FC-SP. A metropolitan-area network can have propagation delays of a few ms, but this is not reasonable for a wide-area network. Within the continental U.S. alone, propagation delays can exceed 30 ms, so there is no point in using a fast-reacting pricing mechanism if FC-SP is possible. Of course, this conclusion depends on some of our other parameters. An obvious assumption to examine is that the average on- and off-periods are 100 and 200 ms, respectively, yielding an average time between the beginning of successive on-periods of 300 ms. It is the ratio of this number to propagation delay that really matters. For FC-FP to be beneficial at 30 ms instead of 5 ms, one need only change the mean time between successive on-periods from 300 ms to 1800 ms. In this case, an FC-FP pricing mechanism would be calculating prices on the order of seconds, which is not excessive. In fact, with on and off periods this long, it would not be a problem to initiate the transmission of a new stream-oriented best effort stream for every on-period, and terminate it every off-period, which would cause FC-FP and FC-SP to yield identical performance.

Another parameter worth exploring is the maximum rate per stream, which we had previously assumed to be 10 Mb/s. (This is equivalent to changing the maximum link throughput, since it is the ratio of these two numbers that matters.) Figure 6 shows total value as a function of the maximum rate with a propagation delay of 10 ms and N=45 streams. The effects of increasing maximum rate are similar to the effects of increasing the number of streams as shown in Figure 4. It is more effective to have dynamic usage-based pricing (SP and FP) than not (NP), except where all streams are of roughly equal value (a=0). Fast-reacting pricing slightly outperforms slow-reacting pricing. Figure 7 shows the case where the maximum rate of each stream is varied, but the number of sources is also varied so that the average load on the link remains fixed. Here we see that if the maximum rate becomes extremely large, so the number of streams becomes quite small (e.g. 4 streams at 120 Mb/s), then fast-reacting pricing becomes much more effective relative to slow-reacting pricing. To see the reason, let j be the number of streams that are in the on-state and transmitting at maximum rate when the link's throughput is maximized. Price is set such that the k most valuable streams will choose to transmit if they are in the on-state, $k \geq j$. If j and k are

large, the number of sources in the on-state at any given time will be fairly close to j. If k and j are small, the coefficient of variation of the number of streams in the on-state is much greater. Thus, fast-reacting pricing, which adjusts to such changes, becomes more effective. However, in the near term, it seems unlikely that there will be much use of such high-data-rate applications. In the long term, high-data-rate streams will become more common, but link capacities will also increase, so it still may not be the case that a small number of streams can consume all of a link's capacity. It therefore remains to be seen whether this effect will limit the effectiveness of slow-reacting pricing.

Other factors were not found to alter the conclusions described thus far in this section. Figure 8 shows the impact of the fraction of time each source is in the on-period (with the sum of mean on- and off-periods held at 300 ms), and Figure 9 shows the slope at which throughput degrades as load increases when the network is congested. In both cases, dynamic pricing greatly outperforms non-usage-based pricing except when all streams are of equivalent value, but fast-reacting pricing does not significantly outperform slow-reacting pricing.

When slope m is small, the magnitude of performance degradation during periods of congestion is low. Figure 9 shows that a small m (e.g. below 0.2) makes usage-based pricing less important, and it makes congestion control unimportant.

5 Conclusion

We have evaluated the network's ability to maximize total system value (social welfare) despite potential congestion, through use of a variety of mechanisms. These include slow- and fast-reacting congestion control, and slow- and fast-reacting pricing. We have seen that, in many ways, dynamic pricing is an alternative to congestion control, and vise versa, since both allow the network to avoid and alleviate congestion. Dynamic state-dependent pricing has an important additional advantage; it allocates resources to the more valuable streams, so pricing is more effective when the value of streams varies significantly from stream to stream. Congestion control was found to be somewhat more effective than pricing if all streams are of comparable value, so there is a throughput penalty for pricing. (In the vocabulary of MacKie-Mason, Murphy, and Murphy [11], maximizing economic efficiency means degrading network efficiency.)

In most cases, when fast-reacting congestion control is used and propagation delay is significant, there is little difference between fast-reacting pricing and slow-reacting pricing. This would certainly be the case in a wide-area network. The one notable exception where the fast-reacting approach does much better is if there are a small number of streams capable of transmitting at very high data rates, consuming much of the congested link's capacity. Slow-reacting pricing is also more attractive to users, it is easier to implement, and less communications capacity is spent on the exchange of pricing information. Consequently, in many cases, slow-reacting pricing will prove preferable to its fast-reacting counterpart. The attraction of fast-reacting pricing in previous work comes in part from the fact that the scenarios considered have involved negligible propagation delay. Of course, other issues must still be addressed to determine the practicality of dynamic state-dependent pricing, whether it is slow-reacting or fast-reacting.

Slow-reacting dynamic pricing is only possible if the network can determine how many streams are passing through a given congested link. This is difficult if the network is not explicitly informed when best-effort streams begin and end. This is one piece of evidence supporting our assertion that networks should offer stream-oriented best-effort services and corresponding pricing. With this approach, a customer would be charged based on both the duration of a stream and the number

of packets sent, and both these prices would be affected by the declared arrival process. Although these services offer no performance guarantees, they provide price incentives for users to indicate the arrival processes of their streams and the performance objectives before transmissions begin. This allows the network to know the number of streams on any link, average data rates, and burstiness. Slow-reacting pricing is just one of the schemes that becomes practical when stream-oriented best-effort services make this information easily accessible to the network. Sophisticated traffic control approaches like [3, 4] can also be used more extensively, thereby allowing the network to meet given performance objectives while carrying more traffic. The final important advantage of stream-oriented best effort traffic is that there can be price disincentives for bursty traffic.

This paper is the first step in investigating the utility of dynamic pricing. Simply by considering propagation delay, we have shown that fast-reacting pricing is of limited value. Future work must relax more assumptions, e.g. examine networks with multiple bottlenecks and more diverse streams, to determine the value of dynamic pricing.

References

- [1] F. P. Kelly, "Charging and Accounting for Bursty Connections," *Internet Economics*, J. Bailey and L. McKnight eds., MIT Press, 1997, pp. 253-78.
- [2] H. Varian and J. K. MacKie-Mason, "Pricing the Internet," Proc. Public Access to the Internet,
 B. Kahin and J. Keller, eds., Englewood Cliffs, NJ: Prentice Hall, 1995.
- [3] J. M. Peha, "Scheduling and Admission Control for Integrated-Services Networks: The Priority Token Bank," Computer Networks, vol. 31, pp. 2259-76, 1999. See www.ece.cmu.edu/~peha/papers.html
- [4] M. A. Lynn and J. M. Peha, "Priority Token Bank Scheduling in a Network of Queues," Proc. IEEE International Conference on Communications (ICC), June 1997, pp. 1387-91. See www.ece.cmu.edu/~peha/papers.html
- [5] J. M. Peha and F. A. Tobagi, "Cost-Based Scheduling and Dropping Algorithms to Support Integrated Services," *IEEE Trans. Commun.*, vol. 44, no. 2, Feb. 1996, pp. 192-202. See www.ece.cmu.edu/~peha/papers.html
- [6] J. Hyman, A. A. Lazar, and G. Pacifici, "Real-Time Scheduling with Quality of Service Constraints," IEEE J. Select. Areas Commun., vol. 9, No 7, Sept. 1991, pp. 1052-63.
- [7] D. Lee and B. Sengupta, "Queueing Analysis of a Threshold Based Priority Scheme for ATM Networks," *IEEE/ACM Trans. Networking*, vol. 1, no. 6, pp. 709-17, Dec. 1993.
- [8] J. M. Peha, "Heterogeneous Criteria Scheduling: Minimizing Weighted Number of Tardy Jobs and Weighted Completion Time," Computers and Operations Research, vol. 22, no. 10, Dec. 1995, pp. 1089-1100. See www.ece.cmu.edu/~peha/papers.html
- [9] R. Cocchi, S. Shenker, D. Estrin, and L. Zhang, "Pricing in Computer Networks: Motivation, Formulation, and Example," *IEEE/ACM Trans. Networking*, vol. 1, no. 6, pp. 614-27, Dec. 1993.
- [10] J. F. MacKie-Mason and H. Varian, "Pricing Congestible Network Resources," *IEEE J. Select. Areas Commun.*, vol. 13, no. 7, Sept. 1995, pp. 1141-49.
- [11] J. F. MacKie-Mason, L. Murphy, and J. Murphy, "The Role of Responsive Pricing in the Internet," Internet Economics, J. Bailey and L. McKnight eds., MIT Press, 1997, pp. 1141-9.

- [12] A. Gupta, D. O. Stahl, and A. B. Whinston, "A Priority Pricing Approach to Manage Multi-Service Class Networks in Real-Time," *Internet Economics*, J. Bailey and L. McKnight eds., MIT Press, 1997, pp. 323-52.
- [13] R. J. Edell, N. Mckeown, and P. P. Varaiya, "Billing Users and Pricing for TCP," *IEEE J. Select. Areas Commun.*, vol. 13, no. 7, Sept. 1995, pp. 1162-75.
- [14] Q. Wang and J. M. Peha, "State-Dependent Pricing and its Economic Implications," accepted to appear in *Telecommunications Systems: Modeling, Analysis, Design, and Management.*
- [15] K. Danielsen and M. Weiss, "User Control Nodes and IP Allocation," Internet Economics, J. Bailey and L. McKnight eds., MIT Press, 1997, pp. 305-21.
- [16] S. Jordan and H. Jiang, "Connection Establishment in High-Speed Networks," *IEEE Journal on Selected Areas in Communications*, vol. 13, no. 7, Sept. 1995, pp. 1150-61.
- [17] S. H. Low and P. P. Varaiya, "A New Approach to Service Provisioning in ATM Networks," *IEEE/ACM Transactions on Networking*, vol. 1, no. 5, pp. 547-53, Oct. 1993.
- [18] J. M. Peha and S. Tewari, "The Results of Competition Between Integrated-Services Telecommunications Carriers," *Information Economics and Policy*, Special Issue on Media and Multimedia, Vol. 10, No. 1, March 1998, pp. 127-55. See www.ece.cmu.edu/~peha/papers.html
- [19] J. M. Peha, "The Need for Service Differentiation in ATM Networks," International Engineering Consortium Annual Review of Communications, vol. 49, 1996, pp. 603-8.
- [20] Q. Wang, J. M. Peha, and M. Sirbu, "Optimal Pricing for Integrated-Services Networks with Guaranteed Quality of Service," *Internet Economics*, J. Bailey and L. McKnight eds., MIT Press, 1997, pp. 353-76. See www.ece.cmu.edu/~peha/papers.html
- [21] D. D. Clark, "Adding Service Discrimination to the Internet," Telecommunications Policy, vol. 20, no. 3, pp. 169-81, Apr. 1996.
- [22] D. D. Clark, "Internet Cost Allocation and Pricing," Internet Economics, J. Bailey and L. McKnight eds., MIT Press, 1997, pp. 215-52.
- [23] H.-P. Chao and R. Wilson, "Priority Services: Pricing, Investment, and Market Organization," The American Economic Review, vol. 77, no. 5, pp. 899-916, Dec. 1987.
- [24] J. M. Peha, "Retransmission Mechanisms and Self-Similar Traffic," Proc. IEEE/ACM/SCS Communication Networks and Distributed Systems Modeling and Simulation Conference, Jan. 1997, pp. 47-52. See www.ece.cmu.edu/~peha/papers.html
- [25] S. Floyd and A. Romanow, "Dynamics of TCP Traffic Over ATM Networks," *IEEE J. Sel. Areas Commun.*, vol. 13, no. 4, pp. 633-41, May 1995.

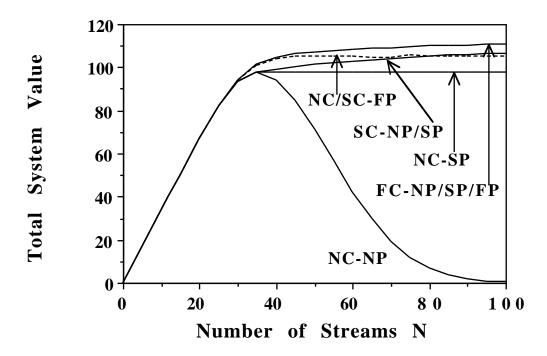


Figure 1: Total value (system throughput) vs. number of streams N. $V_i \propto i^0$. Propagation delay P=10 ms. Mean on-period = 100 ms. Mean off-period = 200 ms. Max rate per source = 10 Mb/s. Max link throughput = 120 Mb/s. m=1.

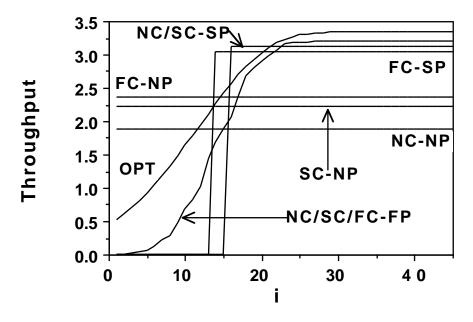


Figure 2: Throughput of each stream $i.\ V_i \propto i^1$. Propagation delay P=10 ms. N=45 streams. Mean on-period = 100 ms. Mean off-period = 200 ms. Max rate per source = 10 Mb/s. Max link throughput = 120 Mb/s. m=1.

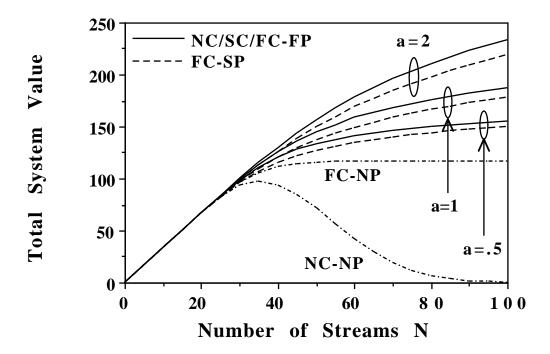


Figure 3: Total value vs. number of streams N. Propagation delay P=1 ms. $V_i \propto i^a$. Mean on-period = 100 ms. Mean off-period = 200 ms. Max rate per source = 10 Mb/s. Max link throughput = 120 Mb/s. m=1.

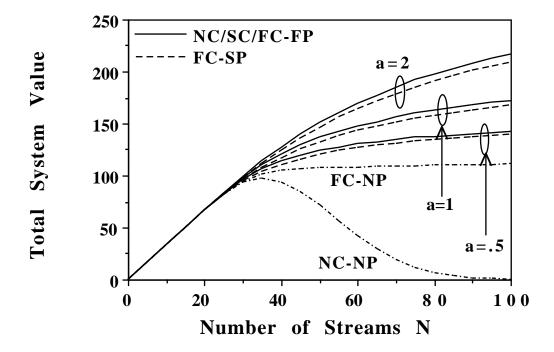


Figure 4: Total value vs. number of streams N. Propagation delay P=10 ms. $V_i \propto i^a$. Mean on-period = 100 ms. Mean off-period = 200 ms. Max rate per source = 10 Mb/s. Max link throughput = 120 Mb/s. m=1.

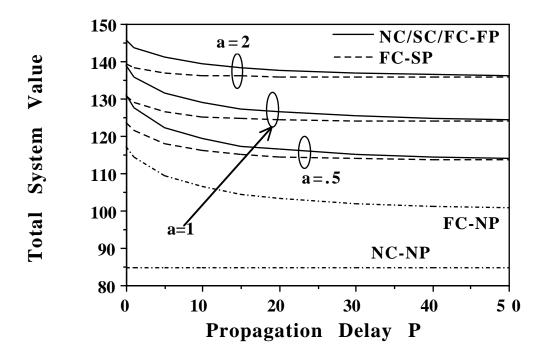


Figure 5: Total value vs. propagation delay P. $V_i \propto i^a$. N=45 streams. Mean on-period = 100 ms. Mean off-period = 200 ms. Max rate per source = 10 Mb/s. Max link throughput = 120 Mb/s. m=1.

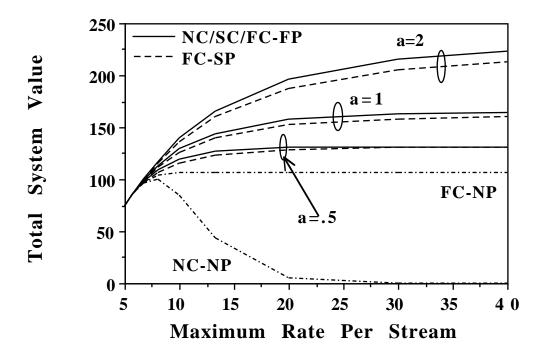


Figure 6: Total value vs. max rate per source. $V_i \propto i^a$. Propagation delay P=10 ms. N=45 streams. Mean on-period = 100 ms. Mean off-period = 200 ms. Max link throughput = 120 Mb/s. m=1.

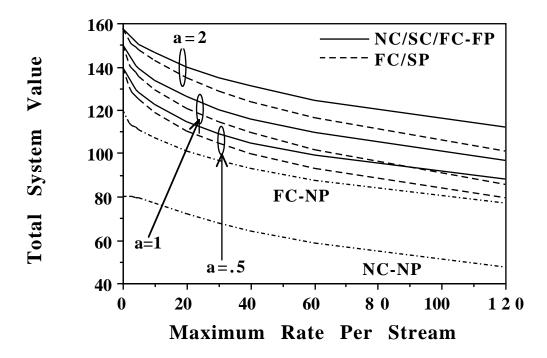


Figure 7: Total value vs. max rate per source. (Number of sources) \cdot (Max rate per source) = 4800 Mb/s. $V_i \propto i^a$. Propagation delay P = 10 ms. Mean on-period = 100 ms. Mean off-period = 200 ms. Max link throughput = 120 Mb/s. m = 1.

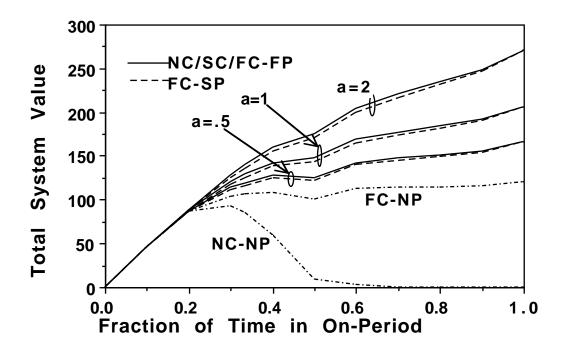


Figure 8: Total value vs. fraction of time each source is on. Propagation delay $P=10 \text{ ms. } V_i \propto i^a$. N=45 streams. Mean on-period + mean off-period = 300 ms. Max rate per source = 10 Mb/s. Max link throughput = 120 Mb/s. m=1.

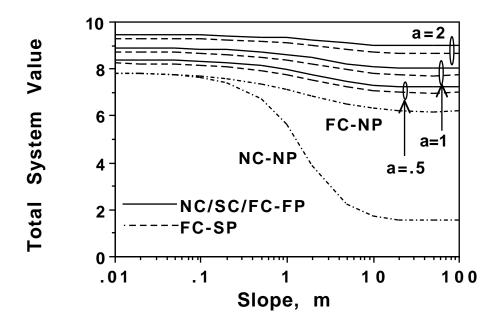


Figure 9: Total value vs. slope m at which throughput declines with load. Propagation delay $P=10 \text{ ms. } V_i \propto i^a$. N=45 streams. Mean on-period + mean off-period = 300 ms. Max rate per source = 10 Mb/s. Max link throughput = 120 Mb/s.