Effect of Pricing Intervals on the Congestion-Sensitivity of Network Service Prices

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Abstract— **Congestion-sensitive pricing schemes for wide area networks have attracted significant attention over the last decade. Several proposals have been made for congestion-sensitive pricing of the Internet. One key implementation obstacle for these dynamic pricing schemes is the necessity of frequent price updates whereas the structure of wide area networks does not allow frequent price updates since round-trip-times are very large for some cases. As the networks allow infrequent price updates, more control is achieved by the pricing schemes with more frequent price updates. So an important issue to investigate is to find a maximum value for the interval (i.e. *pricing interval*) over which price updates occur, such that the level of congestion control can remain in a desired range. This paper presents our modeling and analysis work for the length of pricing intervals. To represent the level of control over congestion, we use correlation between prices and congestion measures. After developing an approximate model for the correlation, we find and prove that the correlation degrades at most inversely proportional to an increase in the pricing interval. We also find that the correlation degrades with an increase in mean or variance of the incoming traffic.**

Keywords— **Network Pricing, Congestion-Sensitive Pricing, Congestion Control, Quality-of-Service**

I. Introduction

One proposed method for controlling congestion in wide area networks is to apply *congestion-sensitive pricing* [1], [2]. Many proposals have been made to implement dynamic pricing over wide area networks and the Internet [3], [4], [5], [6], [7], [8], [9], [10], [11], [12], [13], [14]. Most of these schemes aimed to employ congestion pricing. The main idea of congestion-sensitive pricing is to update price of the network service dynamically over time such that it increases during congestion epochs and causes users to reduce their demand. So, implementation of congestion-sensitive pricing protocols makes it necessary to change the price after some time interval, what we call *pricing interval*.

Clark's Expected Capacity Contracting [3] scheme proposes long-term contracts as the pricing intervals. Kelly's packet marking scheme [5] proposes shadow prices to be fed back from network routers which has to happen over some time interval. MacKie-Mason and Varian's Smart Market scheme [6] proposes price updates at interior routers which cannot happen continuously and have to happen over some time interval. Odlyzko's Paris Metro Pricing scheme [8] proposes fixed prices for different subclasses of network service, but congestion-sensitivity of the prices can only be achieved by updating them over some time interval. Wang and Schulzrinne's RNAP [9] framework proposes to update the price at each service level agreement which has to happen over some time interval. Hence, congestion-sensitive pricing can only be implemented by updating prices over some time interval, i.e. pricing interval.

It has been realized that there are numerous implementation problems for dynamic or congestion-sensitive pricing schemes, which can be traced into pricing intervals. We can list some of the important ones as follows:

- *Users do not like price fluctuations:* Currently, most ISPs employ flat-rate pricing which makes individual users happy. Naturally, most users do not want to have a network service with a price changing dynamically. In [15], Edell and Varaiya proved that there is a certain level of desire for quality-of-service. However, in [16] and [17], Odlyzko provides evidence that most users want simple pricing plans and they easily get irritated by complex pricing plans with frequent price changes. So, it is important that price updates should happen as less as possible. In other words, users like a service with *larger* pricing intervals.

- *Control of congestion degrades with larger pricing intervals:* Congestion level of the network changes dynamically over time. So, the more frequent the price is updated, the better the congestion control. From the provider's side, it is easier to achieve better congestion control with *smaller* pricing intervals.

- *Users want prior pricing:* It is also desired by the users that price of the service must be communicated to them

This work is sponsored by NSF under contract number ANI9819112 and co-sponsored by Intel Corporation.

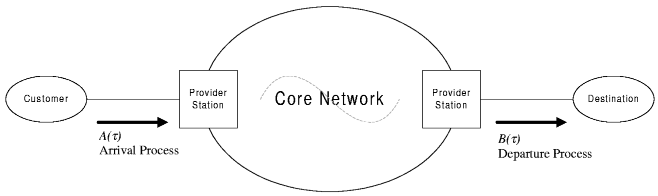

Fig. 1. A sample customer-provider network.

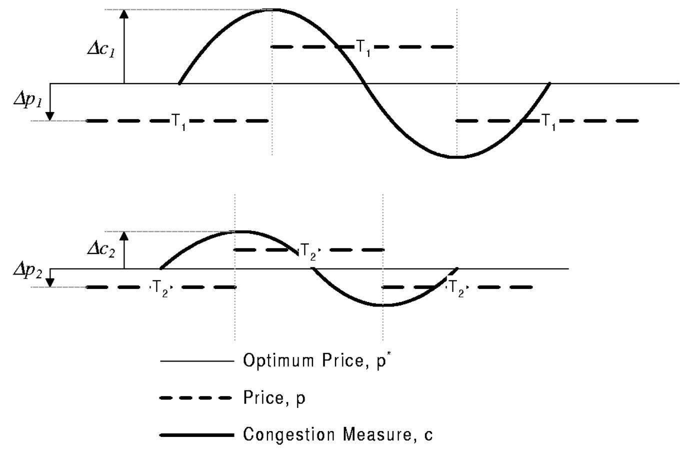

Fig. 2. Congestion measure relative to congestion-sensitive prices in a steady-state network being priced.

before it is charged. This makes it necessary to inform the users of the network service before applying any price update. So, the provider has to handle the overhead of that price communication. The important thing is to keep this overhead as less as possible, which can be done with *larger* pricing intervals.

Hence, length of pricing intervals is a key issue for the implementation of congestion-sensitive pricing protocols. In this particular work, we focus on modeling and analysis of pricing intervals to come up with a maximum value for it such that the level of congestion control remains in an acceptable range. Beyond this range, pricing could be used to regulate demand, but it becomes less useful as a tool for congestion management. The rest of the paper is organized as follows: In Section II, we first explore steady-state dynamics of congestion-sensitive pricing with a detailed look at the behavior of prices and congestion relative to each other. We then develop and discuss an approximate analytical model for the correlation of prices and congestion measures in Section III. In Section IV, we validate the model by simulation experiments and present the results. Finally, in Section V we discuss the implications of the work and possible future work.

II. Dynamics of Congestion-Sensitive Pricing

This section explains the behavior of congestion-sensitive prices and congestion measures relative to each other in a steady-state system. A sample scenario is described in Figure 1. The provider employs a pricing interval of T to implement congestion-sensitive pricing for its service. The customer uses that service to send traffic to the destination through the provider's network. The provider observes the congestion level, c, in the network core and adjusts its advertised price, p, according to it. Note that c and p are in fact functions of time (i.e. $c(t)$ and $p(t)$ where t is time), but we use c and p throughout the paper for simplicity of notation. It is a realistic assumption to say that the provider can observe the network core over small time intervals, i.e. a few round-trip-times (RTTs). To understand effect of pricing interval to the dynamics of congestion-sensitive pricing, we look at the relationship between c and p over time.

Assuming that we have continuous knowledge of congestion level, c, we can represent the dynamics of congestion-sensitive pricing as in Figure 2. Figure 2 represents the relationship between c and p for two different pricing interval lengths, $T_1 > T_2$. For both lengths, the steady-state behavior of congestion-sensitive pricing is represented. The advertised price, p, varies around an optimum price, p^*.

When the provider sees that the congestion level has been decreasing, it decreases the advertised price such that the network resources are not under-utilized. Then the customer starts sending more traffic in response to the decrease in price, and congestion level in the core starts increasing accordingly. The congestion level continues to increase until the price is increased by the provider at the beginning of the next pricing interval. When the provider increases price because of the increased congestion in the last pricing interval, the customer starts sending less traffic than before. Then congestion level starts decreasing. This behavior continues on in steady-state. This explains how congestion-sensitive prices can control the congestion in a network. The important difference is that with a larger pricing interval the congestion level oscillates larger as represented in Figure 2.

Another important characteristic of congestion-sensitive pricing is that the price must be oscillating around an optimum price, p^*, to guarantee both congestion control and high utilization of network resources. In other words, the average of advertised prices must be equal to the optimum price value. Assuming that the customer has a budget of B for network service per unit time and the network has a capacity of Cap per unit time, we can formulate the optimum

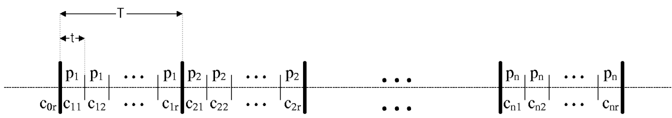

Fig. 3. Prices and congestion measures for subsequent observation intervals.

price as follows:

$$p^* = \frac{B}{Cap} \quad (1)$$

Notice that the customer will send less traffic which will under-utilize network resources when $p > p^*$, and the customer will send excessive traffic than the network can handle which will cause uncontrolled congestion when $p < p^*$. So the provider needs to satisfy the condition that the average of advertised prices equals to the optimum price stated in Equation 1, which requires accuracy in budget estimation. Inaccuracy in budget estimation may result in uncontrolled congestion or very large transient phases before the congestion-sensitive pricing algorithm finds the optimum price value.

The important issue to realize is that congestion control becomes better if the similarity between the advertised price and congestion level is higher. Because of the above explained implementation constraints, the advertised price cannot be updated continuously. This results in dissimilarity between the price and congestion level. Intuitively, if the correlation between the advertised prices and the congestion measures is higher, fidelity of control over congestion becomes higher. Again by intuition, the correlation becomes smaller if the pricing interval is larger.

Another important issue is the *price oscillation* caused by the discontinuous price updates. As the pricing intervals get larger, the oscillation in price also gets larger. This in effect leads to oscillation in user demand (i.e. traffic) correspondingly. So, larger oscillations in price are expected to cause larger oscillation and *higher variance* in incoming traffic. Then, more oscillated traffic causes more oscillated congestion level. This behavior is represented in Figure 2 with the case that $\triangle c_1 > \triangle c_2$ and $\triangle p_1 > \triangle p_2$.

In the next section, we will develop an approximate model of correlation between the advertised prices and congestion measures analytically and find the largest value for the pricing interval such that the system functions in a desired range of service.

III. Analytical Model for Correlation of Prices and Congestion Measures

A. Assumptions and Model Development

Assume the length of pricing interval stays fixed at T over n intervals. Also assume the provider can observe the congestion level at a smaller time scale with fixed observation intervals, t. Assume that $T = rt$ holds, where r is the number of observations the provider makes in a single pricing interval. Assume that the queue backlog in the network core is an exact measure of congestion. [18]

We assume that the customer has a fixed budget for network service and he/she sends traffic according to a counting process, which is a continuous time stationary stochastic process $A(\tau)$,$\tau \geq 0$ with first and second moments of λ_1 and λ_2 respectively. In reality, λ_1 is not fixed, because the customer responds to price changes by changing its λ_1. However, since we assume steady-state and fixed budget for the customer, it is reasonable to say that the customer will send at a constant rate over a large number of pricing intervals. Let m_{ij} be the number of packet arrivals from the customer during the j th observation interval of ith pricing interval, where $i = 1..n$ and $j = 1..r$. So the total number of packet arrivals during the ith pricing interval is

$$m_i = \sum_{s=1}^{r} m_{is} \quad (2)$$

Also assume that the packets leave after the network service according to a counting process, which is a continuous time stationary stochastic process $B(\tau)$,$\tau \geq 0$ with first and second moments of μ_1 and μ_2 respectively. Let k_{ij} be the number of packet departures during the jth observation interval of ith pricing interval, where $i = 1..n$ and $j = 1..r$. So the total number of packet departures during the ith pricing interval is

$$k_i = \sum_{s=1}^{r} k_{is} \quad (3)$$

Assuming that no drop happens in the network core, the first moments of the two processes are equal in steady-state, i.e. $\lambda_1 = \mu_1$, but the second moments are not.

As represented in Figure 3, let p_i be the advertised price and c_{ij} is the congestion measure (queue backlog) at the end of the jth observation in the ith pricing interval. In our model we need a generic way of representing the relationship between prices and congestion. We assumed that the congestion-sensitive pricing algorithm calculates the price for the ith pricing interval according to the following formula

$$p_i = ac_{(i-1)r} \quad (4)$$

where a, *pricing factor*, is a function of pricing interval and observation interval defined by the congestion-sensitive pricing algorithm itself. In our modeling, we assume that a is only effected by the interval lengths, not by the congestion measures. Notice that this assumption does not rule out the effect of congestion measures on the price, rather it splits the effect of congestion measures and interval lengths to the price.

Within this context, the following equations hold:

$$c_{ij} = c_{0r} + \sum_{u=1}^{i-1}(m_u - k_u) + \sum_{s=1}^{j}(m_{is} - k_{is}) \quad (5)$$

$$c_{ir} = c_{0r} + \sum_{j=1}^{i}(m_j - k_j) \quad (6)$$

where $i \geq 1$. Reasoning behind Equations 5 and 6 is that the queue backlog (which is the congestion measure) at the end of an interval is equal to the number of packet arrivals minus the number of packet departures during that interval.

Let the average price be $\overline{p}$ and the average queue backlog be $\overline{c}$. By assuming that the system is in steady-state we can conclude that the following equation is satisfied

$$\overline{p} = a\overline{c} \quad (7)$$

Since the system is assumed to be in steady-state, we can assume the initial (right before the first pricing interval) congestion measure equals to the average queue backlog, i.e.

$$c_{0r} = \overline{c} \quad (8)$$

We want to approximate the model of correlation between p and c according to the above assumptions. We can write the formula for correlation between p and c over n pricing intervals as

$$Corr_n = \frac{E_n[(c-\overline{c})(p-\overline{p})|m,k]}{E_n[(c-\overline{c})^2|m,k]E_n[(p-\overline{p})^2|m,k]} \quad (9)$$

assuming that total of m packet arrivals and k packet departures happen during the n rounds.

We can calculate the numerator term in Equation 9 as follows:

$$E_n[(c-\overline{c})(p-\overline{p})|m,k] = \frac{1}{rn}\sum_{i=1}^{n}\sum_{j=1}^{r}(p_i-\overline{p})(c_{ij}-\overline{c}) \quad (10)$$

By applying Equations 4, 7 and 8 into Equation 10 we can get

$$E_n[(c-\overline{c})(p-\overline{p})|m,k] = \frac{1}{rn}\sum_{i=1}^{n}\sum_{j=1}^{r}(ac_{(i-1)r} - ac_{0r})(c_{ij} - c_{0r}) \quad (11)$$

Then by applying Equations 5 and 6 into Equation 11, we get the following

$$E_n[(c-\overline{c})(p-\overline{p})|m,k] = \frac{a}{rn}\sum_{i=1}^{n}\sum_{j=1}^{r}\left(c_{0r} + \sum_{\theta=1}^{i-1}(m_\theta - k_\theta) - c_{0r}\right)\left(\sum_{u=1}^{i-1}(m_u - k_u) + \sum_{s=1}^{j}(m_{is} - k_{is})\right) \quad (12)$$

After going through the derivation, we can put Equation 12 into the following form

$$E_n[(c-\overline{c})(p-\overline{p})|m,k] = \frac{a}{rn}\sum_{i=1}^{n}\sum_{j=1}^{r}\left(H_1 + \sum_{\theta=1}^{i-1}(m_\theta - k_\theta)\sum_{s=1}^{j}(m_{is} - k_{is})\right) \quad (13)$$

where $H_1 = \sum_u (m_u-k_u)^2 + \sum_u \sum_{v \neq u} 2(m_u-k_u)(m_v-k_v)$, $u = 1..i-1$ and $v = 1..i-1$.

We can calculate the variance of congestion measures similarly as follows:

$$E_n[(c-\overline{c})^2|m,k] = \frac{1}{rn}\sum_{i=1}^{n}\sum_{j=1}^{r}(c_{ij} - \overline{c})^2 \quad (14)$$

By applying Equations 5 and 8 into Equation 14 we can get

$$E_n[(c-\overline{c})^2|m,k] = \frac{1}{rn}\sum_{i=1}^{n}\sum_{j=1}^{r}\left(\sum_{u=1}^{i-1}(m_u - k_u) + \sum_{s=1}^{j}(m_{is} - k_{is})\right)^2 \quad (15)$$

After going through the derivation, we can put Equation 15 into the following form

$$E_n[(c-\overline{c})^2|m,k] = \frac{1}{rn}\sum_{i=1}^{n}\sum_{j=1}^{r}\left(H_1 + H_2 + 2\sum_{u=1}^{i-1}(m_u - k_u)\sum_{s=1}^{j}(m_{is} - k_{is})\right) \quad (16)$$

where $H_2 = \sum_s (m_{is} - k_{is})^2 + \sum_s \sum_{z \neq s} 2(m_{is} - k_{is})(m_{iz} - k_{iz})$, $s = 1..j$, $z = 1..j$.

We finally can calculate the variance of price as follows:

$$E_n[(p-\overline{p})^2|m,k] = \frac{1}{rn}\sum_{i=1}^{n}\sum_{j=1}^{r}(p_i - \overline{p})^2 \quad (17)$$

By using Equations 4, 6 and 7 into Equation 17 we can get the following

$$E_n[(p-\overline{p})^2|m,k] = \frac{a^2}{n}\sum_{i=2}^{n}\left(\sum_{j=1}^{i-1}(m_j-k_j)\right)^2 \quad (18)$$

Similarly after going through derivation, we can put Equation 18 into the following form

$$E_n[(p-\overline{p})^2|m,k] = \frac{a^2}{n}\sum_{i=2}^{n}H_1 \quad (19)$$

Now we can relax the condition on m and k by summing out probabilities on Equations 13, 16, and 19. Specifically, we need to apply the operation $E_n[x] = \sum_{m_{ij}=0}^{\infty}\sum_{k_{ij}=0}^{m_{ij}+c_{i(j-1)}} E_n[x|m,k]Prob\{A(t) = m_{ij}; B(t) = k_{ij}\}$ for all $i = 1..n$ and $j = 1..r$. This operation is non-trivial because of the dependency between the processes $A(\tau)$ and $B(\tau)$. When we consider the system as a queue, we know that only $M/M/1$ system will have the property of independent arrival and departure processes [19]. Since it has been proven that the Internet traffic cannot be Poisson modeled [20], we can conclude that there should be some dependency (i.e. correlation) between the arrival and departure processes of a network. However, there might also be cases where the correlation is negligible. For example, if the distance between arrival and departure points is more, then the lag between the arrival and departure processes also becomes more which lowers the correlation between them. In any case, this issue needs serious investigation which is out of scope of this paper. So, for simplicity, we assume *independence* between the arrival and departure processes and derive an *approximate* model. According to the above assumptions we relax the condition on m and k, and then substitute $\mu_1 = \lambda_1$ because of the steady-state condition, and get the followings:

$$E_n[(c-\overline{c})(p-\overline{p})] = \frac{atr}{2}(n-1)(2tr\lambda_1^2 - \lambda_2 - \mu_2) \quad (20)$$

$$E_n[(c-\overline{c})^2] = \frac{t}{2}\left[(\lambda_2+\mu_2)(rn+1) - 2t\lambda_1^2(1+r-r^2+r^2n)\right] \quad (21)$$

$$E_n[(p-\overline{p})^2] = \frac{a^2tr}{2}(n-1)(2tr\lambda_1^2 - \lambda_2 - \mu_2) \quad (22)$$

By substituting Equations 20, 22, and 21 into 9 we get the correlation model for the first n rounds as follows:

$$Corr_n = \frac{1}{at}\frac{2}{(\lambda_2+\mu_2)(rn+1) - 2t\lambda_1^2(1+r-r^2+r^2n)} \quad (23)$$

Assuming that σ_A^2 is the variance of the arrival process and σ_B^2 is the variance of the departure process, we can finally rewrite 23 as follows:

$$Corr_n = \frac{1}{at}\frac{1}{(\frac{\sigma_A^2+\sigma_B^2}{2}+\lambda_1^2)(rn+1) - t\lambda_1^2(1+r-r^2+r^2n)} \quad (24)$$

In the next section, we discuss the implications of the model and its beneficial use.

B. Model Discussion

Assuming that the other factors stays fixed, the correlation model developed in the previous section (Equation 24) implies three important results:

1. *The correlation degrades at most inversely proportional to an increase in pricing intervals (T):* For the smallest n value (i.e. 1), denominator of Equation 24 will have $r+1$ as a factor which implies linear decrease in the correlation value while the pricing interval, $T = rt$, increases linearly. Notice that its effect will be less when n is larger.

2. *Increase in traffic variances (σ_A^2 and σ_B^2) degrades the correlation:* From Equation 24, we can observe that the correlation decreases when the variance of the incoming or outgoing traffic increases.

3. *Increase in traffic mean (λ_1) degrades the correlation:* Again from Equation 24, we can see that the correlation decreases while the mean of the incoming traffic increases.

These above results imply that lower pricing intervals must be employed when variance and/or mean of the traffic starts increasing. We validate these three results in Section IV by experiments. Note that the model reveals non-intuitive effect of traffic mean on the correlation. Also, observe that the model incorporates not only the effect of pricing intervals on the correlation, but also the effects of statistical parameters (e.g. traffic mean and variance).

As previously mentioned, the correlation between prices and congestion measures is a representation of the achieved control over congestion. Congestion-sensitive pricing protocols can use such a model to maintain the control at a predefined level by solving the inequality $Corr_n \geq Corr_{min}$ for r, which defines the length of the pricing interval. If feedback from the other end (i.e. egress node in DiffServ [21] terminology) is provided, then such

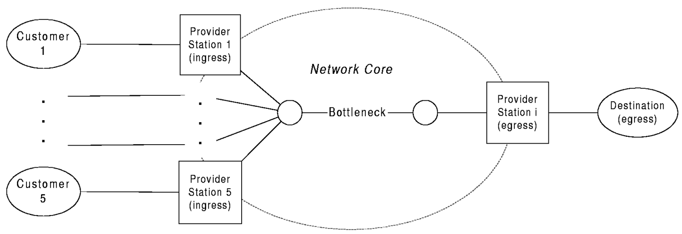

Fig. 4. Topology of the experimental network.

a model can be implemented in real-time. σ_B^2 can be calculated by using the feedbacks from the other end, and σ_A^2 and λ_1 can be calculated by observing the incoming traffic.

IV. Experimental Results and Model Validation

A. Experimental Configuration

We use Dynamic Capacity Contracting (DCC) [22] as the congestion-sensitive pricing protocol in our simulations. DCC provides a contracting framework over Diff-Serv architecture. The provider places its stations at the edge routers of the DiffServ domain. The customers can get network service through these stations by making *short-term contracts* with them. The provider station provides a variety of short-term contracts to the customer and the customer selects the contract which maximizes his/her utility. During the contracts, the station receives congestion information about the network core at a time-scale smaller than contracts. The station uses that congestion information to update the service price at the beginning of each contract. Several price calculations can be implemented in that framework. In our simulation experiments, we use a simple price calculation formula which is based on estimated customer budget and estimated network capacity as stated in Equation 1. The budget estimation is just averaging of the revenues per unit traffic volume earned in previous contracts. We make network capacity estimation by using the received congestion information. The estimated capacity lowers when congestion was detected during the last contract, and vice versa. The contracts in DCC corresponds to the pricing intervals in our modeling.

Figure 4 represents the topology of network in our experiments. There are 5 customers trying to send traffic to the same destination over the same bottleneck with a capacity of 1Mbps. Customers have equal budgets and their total budget is 150 units. We observe the bottleneck queue length and use it as congestion measure. The observation interval is fixed at $t = 80ms$ and RTT for a customer

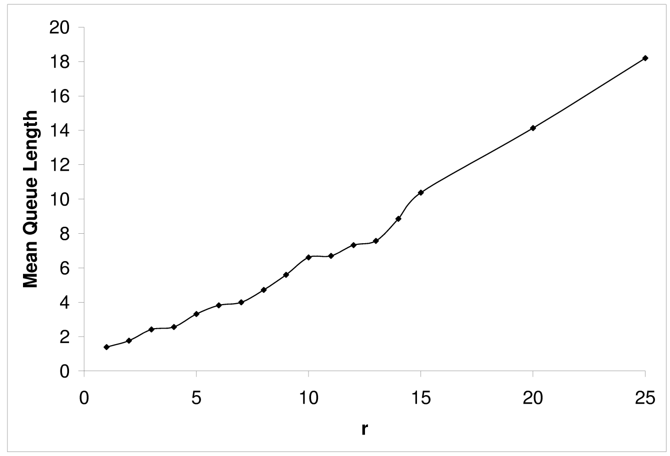

Fig. 5. Mean queue length (in packets) as the pricing interval (in number of observations) increases.

is $20ms$. We increase the pricing interval by incrementing the number of observations (i.e. r) per contract. We run several simulations and calculate correlation between the advertised prices during the contracts and the observed bottleneck queue lengths during the simulations.

Customers send their traffic with a fixed variance but changing mean according to the advertised prices for the contracts. We assume that the customers have fixed budgets per contract with additional leftover from the previous contract. The customers adjust their sending rate according to the ratio B/p where B is the customer's budget and p is the advertised price for the contract. So, customers increase or decrease their sending rate right before the contract starts accordingly. Notice that since the customers' budget is fixed, the sending rate of the customers is actually fixed on long run, which fits to the fixed average incoming traffic rate (λ_1) assumption in the model.

B. Results

In this section, we present several simulation results for validation of the model and the three results it implies.

Figures 5 and 6 show mean and variance of the bottleneck queue length. We can see significant increase (at least linear) in mean and variance of the bottleneck queue as the pricing interval increases linearly. Furthermore, Figure 7 shows the change in the coefficient of variation for the bottleneck queue length as the pricing interval increases. Note that an increase in the coefficient of variation means a decrease in the level of control. We can observe that the coefficient of variation increases as the pricing interval increases until $10r$, and stays fixed there after. This is because the congestion-sensitive pricing protocol looses control over congestion after a certain length of pricing interval, which is $10r$ in this particular experiment. These

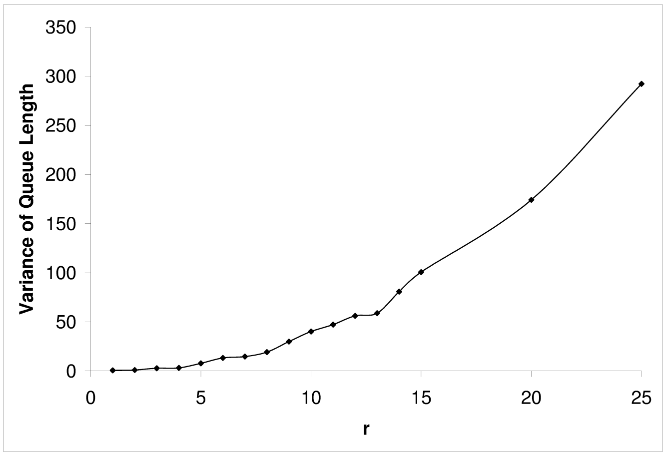

Fig. 6. Variance of queue length as the pricing interval (in number of observations) increases.

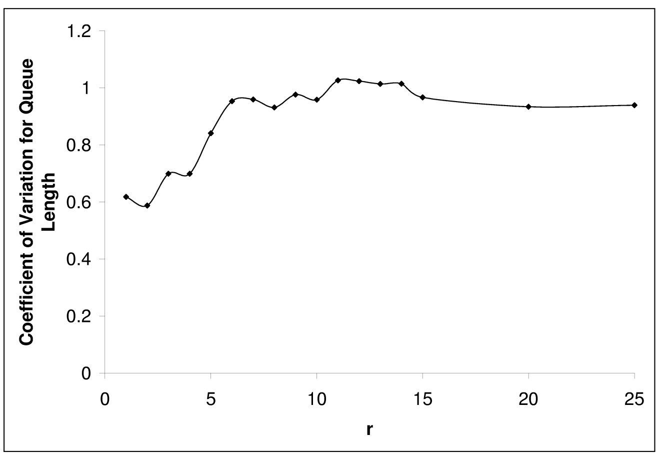

Fig. 7. Coefficient of variation($\frac{\sigma}{\mu}$)of queue length as the pricing interval (in number of observations) increases.

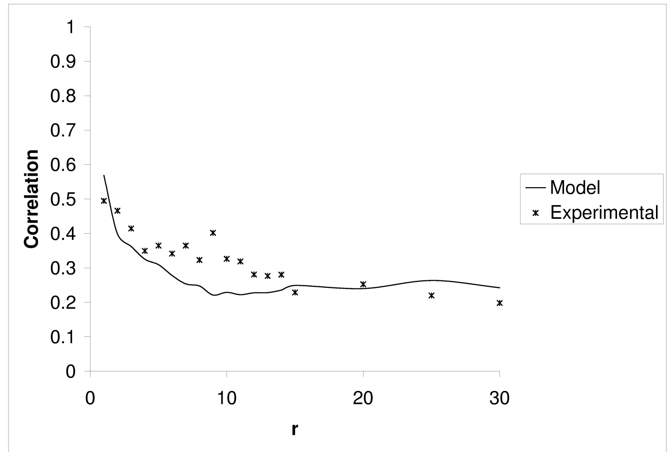

Fig. 8. Fitting analytical model to experimental results for simulation time of 15 pricing intervals.

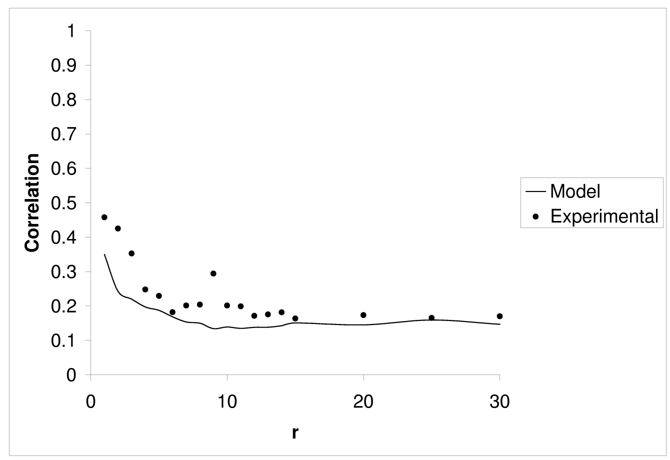

Fig. 9. Fitting analytical model to experimental results for simulation time of 25 pricing intervals.

results in Figures 5 to 7 validate our claim about the degradation of control when pricing interval increases. Furthermore, they also show that dynamic pricing does not help congestion control when the pricing interval is longer than a certain length.

To validate the model, we present the fit between our correlation model and experimental results we obtained from above mentioned simulation configuration. Figures 8 and 9 represent the correlations obtained by inserting appropriate parameter values to the model and corresponding experimental correlations, respectively for the cases $n = 15$ and $n = 25$. Notice that the model is dependent on the experimental results because of the parameters for incoming and outgoing traffic variances (i.e. σ_A^2 and σ_B^2), pricing factor (i.e. a), and mean of the incoming traffic (i.e. λ_1). We first calculate the parameters σ_A^2, σ_B^2, a (ratio of average price by average bottleneck queue length) and λ_1 from the experimental results, and then use them in the model.

We now validate the three results implied in Section III-B. Figures 8 and 9 show that the correlation decreases slower than $1/r$ when the pricing interval (i.e. r) increases linearly. This validates the first result. Figure 11 represents the effect of change in the variance of incoming and outgoing traffic (i.e. σ_A^2 and σ_B^2) on the correlation. The horizontal axis shows the increase in variances of both the incoming and outgoing traffic. The results in Figure 11 for different values of n obviously show that an increase in traffic variances causes decrease in the correlation. This validates the second result. Finally for validation of the third result, Figure 10 represents the effect of change in the mean of the incoming traffic (i.e. λ_1) on the correlation. We can see that increase in λ_1 causes decrease in the correlation. Another important realization is that the correlation is more sensitive to variance changes than mean changes as it can be seen by comparing Figures 10 and 11.

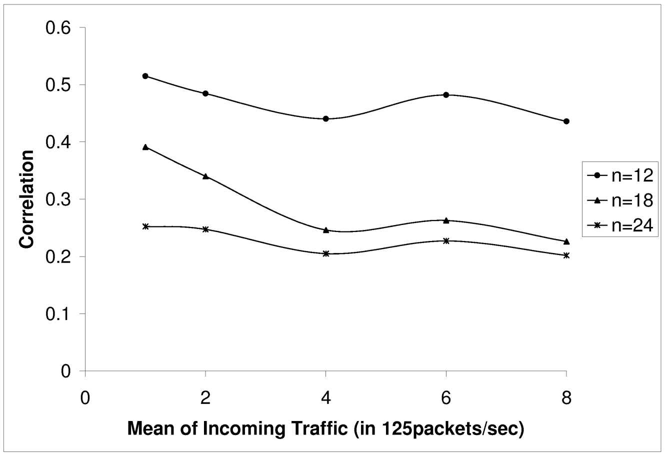

Fig. 10. Effect of change in the mean of the incoming traffic to the correlation for a pricing interval of $800ms$, i.e. $r = 10$.

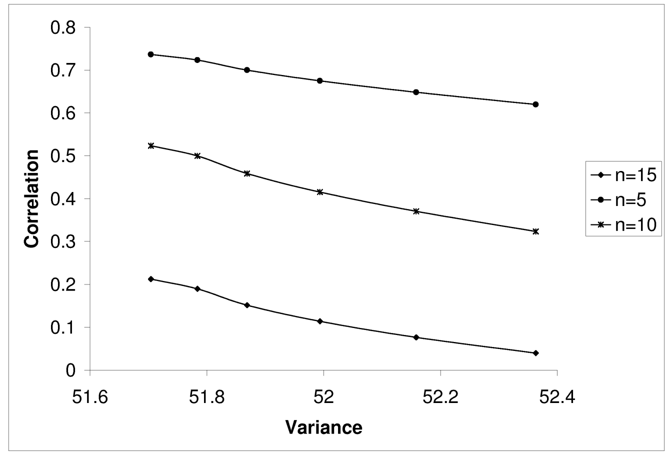

Fig. 11. Effect of change in the variance of the incoming and outgoing traffic to the correlation for a pricing interval of $800ms$, i.e. $r = 10$.

Before concluding this section, we would like to stress on the relationship between the correlation and the level of congestion control. As we previously stated, Figures 8 and 9 show the effect of increasing pricing intervals on the correlation for different values of n. We can see that the correlation value stays almost fixed after the pricing interval reaches to $10r$. Also, Figure 7 shows the coefficient of variation for the bottleneck queue length in the experiments. Remember that coefficient of variation for the queue length represents the level of congestion control being achieved. We observe in Figure 7 that it reaches to its maximum value (approximately 1) when the pricing interval reaches to $10r$, which is the same point where the correlation starts staying fixed in Figures 8 and 9. So, by comparing Figure 7 with Figures 8 and 9, we can observe that the correlation decreases when the level of congestion control decreases, and also it stays fixed when the level of congestion control stays fixed. This shows that the correlation can be used as a metric to represent the level of congestion control.

V. Conclusions and Discussions

We investigated steady-state dynamics of congestion-sensitive pricing in a customer-provider network. With the idea that correlation between prices and congestion measures is a measurement for level of congestion control, we modeled the correlation. We found that the correlation decreases at most inversely proportional to an increase in pricing interval. We also found that the correlation is inversely effected by the mean and variance of the incoming traffic. This implies that congestion-sensitive pricing schemes need to employ very small pricing intervals to maintain high level of congestion control for current Internet traffic with high variance [23].

From the model and also from the simulation experiments we observed that the correlation between prices and congestion measures drops to very small values when pricing interval reaches to 40 RTTs even for a low variance incoming traffic. Currently, we usually have very small RTTs (measured by milliseconds) in the Internet. This shows that pricing intervals should be 2-3 seconds for most cases in the Internet, which is not possible to deploy over low speed modems. This result itself means that deployment of congestion-sensitive pricing over the Internet is highly challenging. As the link speeds are getting higher and RTTs are getting smaller, it becomes harder to deploy congestion-sensitive prices. The results obviously show that there will be need for intermediate middle-ware components (i.e. intermediaries) between individual users and ISPs, when ISPs deploy congestion-sensitive pricing for their service. These middle-ware components will be expected to lower price fluctuations such that price changes will be possible implement over low speed modems. This scenario suggests that congestion-sensitive prices can be implemented among ISPs to control congestion, but there has to be middle-ware components which can handle the transition of the congestion-sensitive prices to the individual customers in a smooth way. Alternatively, instead of using congestion-sensitive pricing directly for the purpose of congestion control, it can be used to improve fairness of an underlying congestion control mechanism. We believe that the second approach is more realistic way of implementing congestion-sensitive pricing over the Internet.

Future work will include complex modeling of the dynamics of congestion-sensitive pricing by relaxing some of the assumptions. For example, a model without fixed arrival rate assumption would represent the behavior of the system more appropriately. Also, better budget models are needed in the model. Additionally, the assumption of independence between the arrival and departure processes must be relaxed to make exact modeling of the system.

Another important issue to explore is how much congestion control can be achieved with exactly what level of correlation between prices and congestion measures. In this paper we assumed that the correlation value is a direct representation of the level of congestion control that was achieved. Although we supported this idea by providing the match between the correlation and the coefficient of variation in Section IV-B, this issue needs more investigation.

ACKNOWLEDGMENTS

We used the network simulator, *ns*, [24] in our simulations. Also thanks to Biplab Sikdar, Satish Raghunath and Sthanunathan Ramakrishnan for their helpful discussions.

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