Towards Optimized QoS Based – Charging Model

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***Abstract*—This paper proposes a pricing model for Differentiated Services (DiffServ) network. The service differentiation is modeled according to the guaranteed QoS level for each class. This model assumes that a user selects an appropriate class of service depending on his QoS requirements. The users access to the service is assumed as bursty traffic, and all the users are competing on one shared bandwidth. The equivalent guaranteed capacity of a class is calculated according to its guaranteed QoS level. A fixed price is given for each class for certain guaranteed capacity. Then, an analysis for the service provider to achieve maximum value of revenues is made by determining the total required shared bandwidth, the service class optimum guaranteed capacity and its optimum price.**

I. INTRODUCTION

Most of the traditional telecommunication networks infrastructure has been created at different times as the business evolved, with different ways and means to access the internal system components. This creates standalone services in the organization. On the other hand, the internal system components typically have mixed pedigree since most of these components were bought from different suppliers and customized to fit the current system requirements. As a result, there is no standard tool set, architecture or hardware platform for those different systems. Therefore, a very tight coupling exists between the services of the network and the network infrastructure itself. This makes it difficult to change one without changing the other.

The evolution of telecommunication technology has accelerated in the past few years. Users have become able to access the packet switching networks faster with the newly developed IP based network technologies. Consequently, new environment of the Next Generation Networks (NGN) has appeared. This environment offers the users a capability to connect to large number of Value Added Service Providers (VASPs). The VASPs can deploy their services (like real-time multimedia streaming, value added location based services or audio/video conferencing) through different access networks. Thus, the NGN systems evolve into a DiffServ network able to accommodate differentiated classes of service to support various types of applications and business requirements [1]. In this new environment, pricing of network services is becoming increasingly important. It helps providers to recover their operating expenses. Also, it can lead to more efficient use of the network resources (e.g., the *bandwidth*) by providing sufficient incentives to users.

Some interesting papers address a number of the topics related to the work presented in this paper. Customers' requirements in heterogonous networks are discussed in [2]. The paper also provides a general framework for all management aspects related to the billing in such environment. In [3] a generic pricing model for Internet services offered by a group of SPs based on revenue-sharing strategy is proposed. The papers [4], [5], [6], [7] discuss the adaptive pricing in different approaches. Pricing of multiple priority class networks has been studied in [4] using a game theoretic model, where the users are free to select the priority class, but they are charged accordingly. The study shows that the price can be used to provide relative QoS guarantees. In addition, a congestion control based scheme is provided in [5] to price similar networks. For that proposed pricing scheme, the congestion control is achieved through the congestion fee, which serves as a signal to the user. Those users who value the service less will drop out when congestion occurs. The network load stays in equilibrium through each user individual, autonomous, and selfish decisions on how to use the network. Also, [6] proposes an adaptive pricing algorithm in a TCP-like network. In this pricing algorithm, the total queuing delay is interpreted as a price. In [7] the price can be updated according to the link congestion and/or source signal quality. An investigation is done in [8] on two different customer populations, quality-sensitive customers and price-sensitive customers. The paper then suggests some solutions in both cases to the SPs helping them to find out the optimum operating price. The roles of pricing DiffServ networks are studied in [9]. Paper [10] concludes that a simple flat-rate pricing scheme competes favorably over complicated pricing schemes.

The present paper, assumes a network model for a service provider offering a service to multiple categories of users through different service classes. Users' categories may differ in their demand pattern and/or their benefit of using the service, which is expressed as their willingness to pay. The service classes are differentiated by the maximum allowed loss rate (i.e., the probability of data losses). All the service classes are accessing the service creation environment (i.e., Application Server) through one shared bandwidth.

In addition to the complexity of dynamic adaptive pricing schemes, fixed pricing scheme can be more efficient [10]. Practically, dynamic pricing schemes are neither understandable nor acceptable by the customers. Therefore, a fixed price is assumed for each service class in the proposed model.

R.Guerin et al., consider an interrupted fluid flow source having a peak bit rate R_{peak}, mean burst period b and utilization fraction ρ, feeds a finite size buffer x, and the smallest allowed buffer overflow probability "*the minimum acceptable data loss rate*" ε. For that source the equivalent capacity, $\widehat{c}$, is given by [11]:

$$\hat{c} \approx \frac{M - x + \sqrt{[M-x]^2 + 4x\rho M}}{2\alpha b(1-\rho)} \quad (1)$$

where $M = \alpha b(1-\rho)R_{peak}$,

$\alpha = \ln(1/\varepsilon)$

For N multiple sources with average bit rate of each source m_i and variance σ_i^2 for each source, the total equivalent capacity is approximated as follows [11]:

$$\hat{c} = \min\{\hat{c}_{(F)}, \hat{c}_{(S)}\} \quad (2)$$

where $\hat{c}_{(F)} = \sum_{i=1}^{N} c_i$,

$$\hat{c}_{(S)} = \sum_{i=1}^{N} m_i + \left(\sqrt{-2\ln(\varepsilon) - \ln(2\pi)}\right)\sqrt{\sum_{i=1}^{N} \sigma_i^2}$$

If we know the customers demand pattern for certain service, the total shared bandwidth at which the service provider expects to get maximum revenue can be determined easily using Equations 1 and 2. Next, the optimum price of each service class is calculated based on the required guaranteed capacity of that class and the customers' willingness to pay.

The rest of the paper is organized as follows. In Section II, different charging strategies for telecommunication services and a customer willingness to pay for these services are discussed. The network model that will be studied and simulated is defined in Section III. A simulation case study and an analysis of its results are presented in the Sections IV and V respectively. Finally, the conclusion of the paper is given in Section VI.

II. SERVICE CHARGING STRATEGIES

In general, telecom services can be charged according to the following strategies: Subscription based charging, usage based charging, or combination of the two. For the first strategy, the price of a service is determined by a constant money value C_{su} on a given time period d_{su}, no matter whether the service is really used or not. In the second strategy, the service is charged only when it is actually used. The usage might be measured in terms of time units d_{tu} with a corresponding charge unit C_{tu} and/or a volume units v_{vu} of charge C_{vu}. Therefore, the total charge of accessing a service for n times, in a given subscription period T, time usage period t_i, and volume usage v_i can be put in the form:

$$C = \frac{C_{su}}{d_{su}}T + \sum_{i=1}^{n}\left[\frac{C_{tu}}{d_{tu}}t_i + \frac{C_{vu}}{v_{vu}}v_i\right] \quad (3)$$

But for a known equivalent capacity $\hat{c}$, the volume usage v can be approximated as follows:

$$v = t \times \hat{c} \quad (4)$$

Therefore Equation 3 can be rewritten as:

$$C = F_s T + (F_t + F_v \hat{c})\sum_{i=1}^{n} t_i \quad (5)$$

where F_s, F_t and F_v are the charging factors and defined as:

$$F_s = \frac{C_{su}}{d_{su}}, F_t = \frac{C_{tu}}{d_{tu}}, F_v = \frac{C_{vu}}{v_{vu}}$$

In the NGN environments a service can be charged according to many newly defined attributes [12]. Some of these attributes are QoS, access network, location, and device capability. Each attribute may split the service into several categories (*classes*). For each class certain charging factors must be defined. The first attribute, QoS level, is the most important one. Most of the other attributes indirectly affect the required QoS. Hence, our classification of the service classes has been made only according to this attribute. The effect of the remaining attributes is considered generally as a random value added to the basic required QoS of the service. Knowing the traffic specification of a certain service, an equivalent guaranteed capacity of each service class with minimum required QoS level (loss rate ε) could be calculated using Equations 1 and 2.

The relationship between customer benefit of using some service and the guaranteed capacity, $\hat{c}$, can be defined and measured in terms of the customer's Willingness To Pay (*WTP*) for that service according to the following formula [13]:

$$WTP = P\hat{c}^r \quad (6)$$

where P is the user potential parameter and r represents the sensitivity of the increase in *WTP* to the increase in the guaranteed capacity.

Customer charging in this paper will be implemented according to a guaranteed *QoS*, which is represented in our model by the equivalent capacity of the service class. Therefore, the charge of accessing a service class SC_k in a session (i) can be calculated in terms of volume usage charging as follows:

$$C_{SC_k}(i) = F_v \hat{c}_{SC_k} t_i \quad (7)$$

Obviously, the customer will accept the service only if its price is less than the value of his *WTP* for that service. For a service class with a guaranteed capacity, $\hat{c}$, the charging factor F_v (or the Price) of that class should be optimized according to the tradeoff between its guaranteed capacity $\hat{c}$ and a customer *WTP* for the service.

III. THE NETWORK MODEL

The proposed network model shown in Figure 1 assumes that N customers can be split into K_u categories. Each category may use the same service offered by an application server through one shared link with total bandwidth c_{tot}, but in a different demand pattern and/or different *WTP*. All of these categories can access the service through K_{sc} service classes sorted in an ascending order by their level of QoS, where $K_{sc} \leq K_u$.

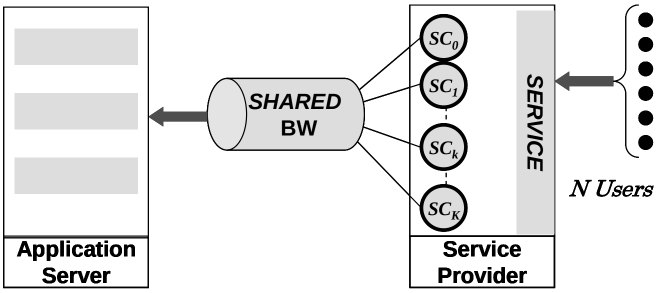

Figure 1 Network Model.

The traffic characteristics of the requested service by any one of the users categories is characterized by the vector (R_{peak}, ρ, b) and the loss rate which is denoted here as *ReqE*, ranged from e_{min} to e_{max}. The users are accessing the service according to random interarrival time. The holding time for the session also is given by a random duration *D*. The potential parameter of a customer *WTP* is represented by a random variable given by a distribution density function *f*(*p*). So, the expected *WTP* for the customer when accessing service class SC_k in a session (i) can be determined as follows:

$$E\left[WTP_{SC_k}(i)\right] = E\left[f(p)\right]\left(\hat{c}_{SC_k}\right)^{r+1} t_i \tag{8}$$

When a customer tries to access a service, the service provider (SP) has to check the requested *QoS* level *ReqE* of that customer, then assigns the first suitable SC_k that has a loss rate less than or equal to the requested *ReqE*. If no such *SC* is found, the customer request will be blocked (b_1). If the SC_k is found, the SP must check the shared bandwidth available. If there is no enough bandwidth for the selected *SC*, the service will be canceled. This action is represented in the proposed model by the blocking probability (b_3). The user is assumed to accept the service only if its price is less than or equal to his *WTP* for that service. The price of accessing the service class SC_k in session (i) and the *WTP* of the customer to access service with guaranteed capacity $\hat{c}_{SC_k}$ can be easily calculated using Equations 7 and 8, respectively. According to the comparison of the user *WTP* and the price of accessing the service, the user can make a decision about whether he/she wishes to continue with the service or not. If the user decides to cancel the service, this action is considered as the blocking probability (b_2) for service delivery.

Therefore, the probability of a successful service delivery of the customer request, *P*(*S*), is given by:

$$P(S) = 1 - P(B) \tag{9}$$

where $P(B) = P(b_1 \cup b_2 \cup b_3)$

To determine the probability $P(b_1)$, consider the case of a service class with loss rate ε, and a customer that can select his required a loss rate as a random variable *ReqE* defined by a distribution density function *E*(*e*). Then the probability $P(b_1)$ for this *SC* can be defined as:

$$P(b_1) = P(e \le \varepsilon) = \int_{e_{\min}}^{\varepsilon} E(e)\,de \tag{10}$$

From Equation 10, it is clear that $P(b_1)$ will increase as the value ε for *SC* increases or as the guaranteed capacity $\hat{c}$ of this *SC* is decreased. Assuming that the equivalent capacity of *ReqE* value selected by a customer can be fitted by a distribution density function $\hat{C}(\hat{c})$. Thus, $P(b_1)$ can be expressed in terms of the equivalent capacity required by the customer and the guaranteed capacity of the service class $\hat{c}_{SC_k}$ as follows:

$$P(b_1) = P\left(\hat{c} > \hat{c}_{SC_k}\right) = 1 - \int_{\hat{c}_{\min}}^{\hat{c}_{SC_k}} \hat{C}(\hat{c})\,d\hat{c} \tag{11}$$

The second blocking probability $P(b_2)$, can be defined as follows:

$$P(b_2) = P\left(WTP_{SC_k}(i) - C_{SC_k}(i) < 0\right)$$

or,

$$P(b_2) = \int_0^{F_v / (\hat{c}_{SC_k})^r} f(p)\,dp \tag{12}$$

Assuming that the interarrival time of customers to certain service is represented by continuous random variable with a distribution density function *A*(*t*) and the holding time for each customer is random defined by a continuous density function *D*(*t*). Therefore, the random density function *N*(*n*) of the number of customers in the system at any time can be found numerically. Then, the random distribution of a total equivalent capacity required for *N*(*n*) also can be found numerically by using Equations 1 and 2. Assume that, this distribution is $C_t(c)$, then the probability of b_3 for a total bandwidth C_{tot} can be expressed by:

$$P(b_3) = 1 - \int_0^{C_{tot}} C_t(c)\,dc \tag{13}$$

Defining the cost of total capacity as:

$$cost = A\left(C_{tot}\right)^s \tag{14}$$

where *A* and *s* represents the potential and sensitivity parameters respectively for the total capacity cost function.

Clearly, $P(b_3)$ gets closer to zero as C_{tot} increases. On the other hand, the cost will increase as C_{tot} increases. Thus, the optimum C_{tot} is the smallest capacity that makes $P(b_3)$ equals to accepted threshold value. The total sales (*s*) of an SP for a certain service class SC_k can be provided as follows:

$$s = E\left[N(u)\right] \times \hat{c}_{SC_k} F_v P(S) \sum_{i=1}^{n} t_i \tag{15}$$

If we assume that $P(b_1 \cup b_3) = \beta$, the probability of a successful service delivery *P*(*S*) can be expressed as:

$$P(S) = 1 - \beta - (1-\beta)\int_0^{F_v / (\hat{c}_{SC_k})^r} f(p)\,dp \tag{16}$$

Then, the optimum volume charging factor F_v of the service is the price that maximize $\hat{c}_{SC_k} F_v P(S)$.

IV. SIMULATION CASE STUDY

The previous section has represented the theoretical background of the problem. A numerical case study will be simulated in this section to compare the simulation results with the mathematical solution.

To make the problem simpler, it is assumed, in this case, that all users request the same service (i.e. the same traffic specification is assumed). Individual parameters used in the simulation are shown in Table 1.

Table 1: The simulation parameters

Parameter	Value
Total capacity cost potential A	10^{-3}
Total capacity cost sensitivity s	0.4
Mean interarrival time of users	60sec
Mean service holding time.	3600sec
Acceptable loss rate of users.	10^{-5} to 10^{-1}
Peak bit rate of the flow	10Mbit/sec
Flow utilization fraction ρ	60%
The mean burst period b	100msec
Buffer size x	10Mbit
SC maximum loss rate	10^{-5}
WTP potential parameter μ_P	2.5×10^{-6}
WTP sensitivity parameter r	0.1

Here, the users' interarrival time is assumed as exponential random variable with mean 60sec. The duration of the service holding time is assumed as an exponential random value with mean 3600sec. The user acceptable loss rate is assumed as a uniform random variable of maxim 10^{-1} and minimum 10^{-5}.For each user, the traffic characteristic vector that specifies the service (R_{peak}, ρ, b) is set to (10Mbit/sec, 0.6, 100msec). Service classes guaranteed maximum loss rate of 10^{-5}, so the blocking probability $P(b_1)$ is zero. The potential parameter of the total capacity cost is assumed 10^{-3}currency_unit/bit.sec, and the sensitivity parameter is assumed as 0.4. Regarding the customers' behavior for the *WTP* function, the potential parameter is assumed as exponential random variables with mean μ_P equals to 2.5×10^{-6}, while the sensitivity parameter is set to 0.1.

V. RESULTS AND OPTIMUM REVENUES OF SP

The service is assumed to be charged according to volume usage strategy with volume charging factor F_v equals to 1.1×10^{-5}.The total capacity of shared link ranges from 6.9722Mbit/sec, which is the equivalent capacity for one user to access the service, to 600Mbit/sec. The relationship between total available bandwidth and bandwidth utilization percent is shown in Figure 2. Figure 3 shows the relationship between total bandwidth and service blocking probability.

When the total capacity ranges from 0 to 250Mbit/sec, all the available capacity is utilized, and then the capacity utilization starts decaying. It is clear that for zero total capacity the blocking probability is 100% and decreases with increasing total capacity as shown in Figure 3. This trend changes when total capacity reaches 200Mbit/sec. For total capacity above 200Mbit/sec, the blocking probability plateaus out at 65%. This can be explained as that there is no more blocking b_3 due to the lack of bandwidth. In other terms, blocking probability becomes independent of the available bandwidth, which has reached a level to accommodate all expected users. This leads to the conclusion that the blocking probability above 200Mbit/sec is due to b_2.

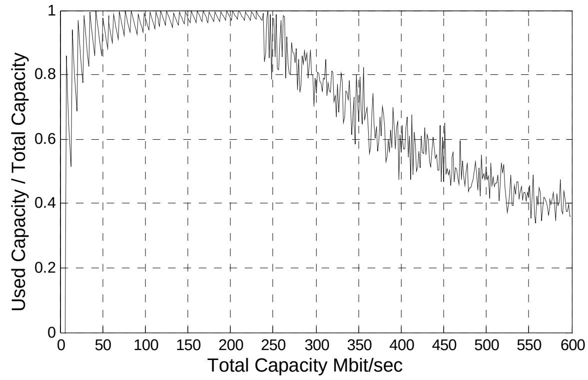

Figure 2 Relation between total capacity and utilized capacity.

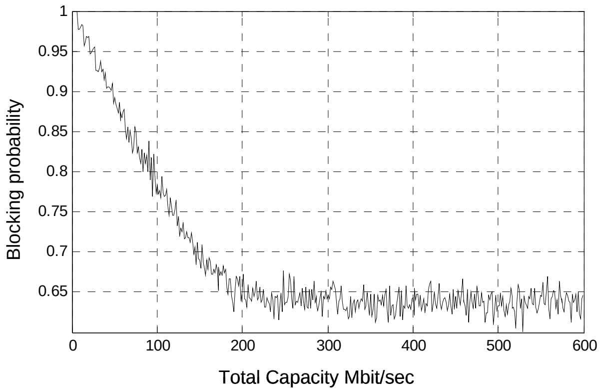

Figure 3 Relation between total capacity and blocking probability.

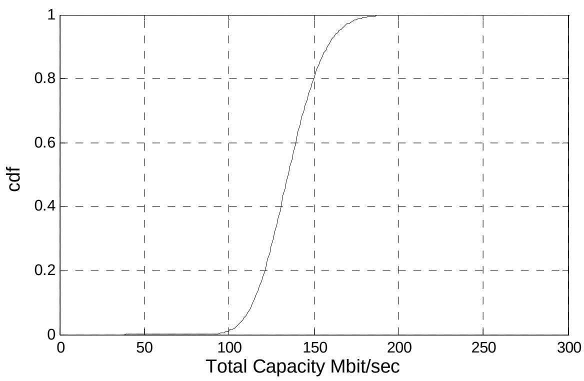

Figure 4 Cumulative Distribution Function (cdf) of the total required capacity in the network.

The distribution of the number of customers in the system was found to be a Poisson random distribution with a mean of 60 customers. This distribution was obtained by fitting a generated data for the number of customers from a system with the same interarrival and holding time of our case study (exponential interarrival time with 60 sec mean and exponential holding time with 3600 sec mean). Using this Poisson distribution for the customers with equation 2, a series of values for the total equivalent capacity was generated. This data was found to fit a Gamma distribution with mean and variance of $1.3463\times10^{8}, 2.9490\times10^{14}$ respectively, as shown in Figure 4.

From this distribution the probability of total capacity to be less than or equal to 210Mbit/sec is 0.9999. In other words, the probability that the total equivalent capacity needed in the system exceeds 210Mbit/sec is very small (10^{-5}). Therefore, the smallest capacity that guarantees $P(b_3)\approx 0$, is 210Mbit/sec.

Figure 5 shows the relation between the total capacity and the total sales. The relation between the total capacity and the revenue ratio (*revenue / total capacity cost*) is shown in Figure 6. From these figures, it is clear that the total amount of sales increases as the total capacity is increased until it reaches the values near 200Mbit/sec, where the total sales seams to be constant even when the total capacity is increased. On the other hand, the revenue ratio is increased as the total capacity increases in the range from 0 to 200Mbit/sec, but it starts decaying after that. So the optimum total capacity is in the range of 200Mbit/sec.

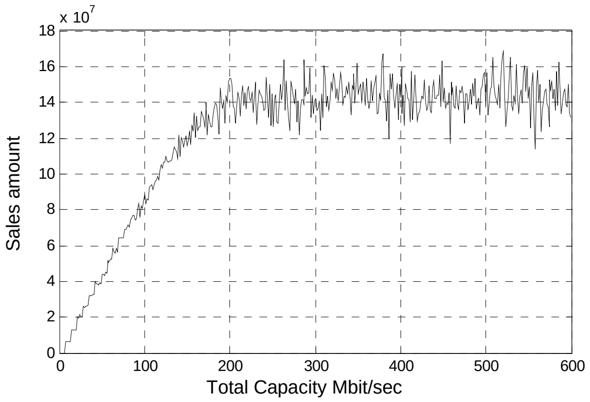

Figure 5 Relation between total capacity and total sales amount.

Next, the total capacity is fixed to the 210Mbit/sec and the service charging parameter *Fv* is varied in the range, from 0 to 1×10^{-4}. From Figure 7, it is clear that the optimum value of F_v is in the range 1×10^{-5} to 1.5×10^{-5}.

Analytically, for an *SC* with maximum allowed loss rate of 10^{-5}, that has been assumed in this simulation case study to be not exceeded by any one of costumers. Using Equation 1 the equivalent capacity for single source will be 6.9722Mbit/second. Also, the total capacity is found to be 210Mbit/sec by substituting the expected number of the customers in the system into Equation 2. This total capacity is sufficient to guarantee that the probability β in Equation 16 is approximately zero. Remembering that the potential parameter of the *WTP* function is assumed to be an exponential random variable with a mean of 2.5×10^{-6}, and the sensitivity parameter is set to 0.1. Therefore by substituting the above parameters into Equation 16, the probability of a successful service delivery will be:

$$P(S) = e^{-F_V \big/ \left(2.5\times10^{-6}\right)\left(6.9722\times10^{6}\right)^{0.1}} \tag{17}$$

So the optimum value of the factor F_v is the one that makes $6.9722\times10^{6}F_v e^{-F_V \big/ \left(2.5\times10^{-6}\right)\left(6.9722\times10^{6}\right)^{0.1}}$ maximum, which is equal to 1.2086×10^{-5}.

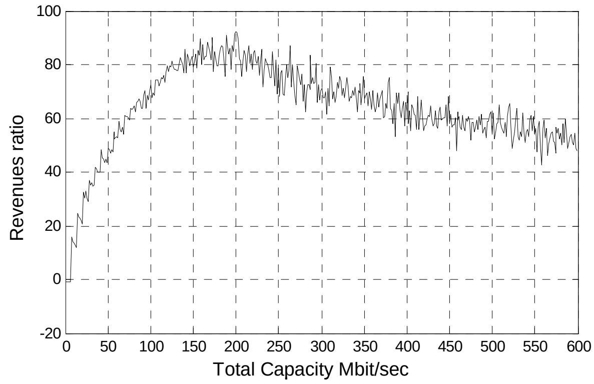

Figure 6 Relation between total capacity and total revenues ratio.

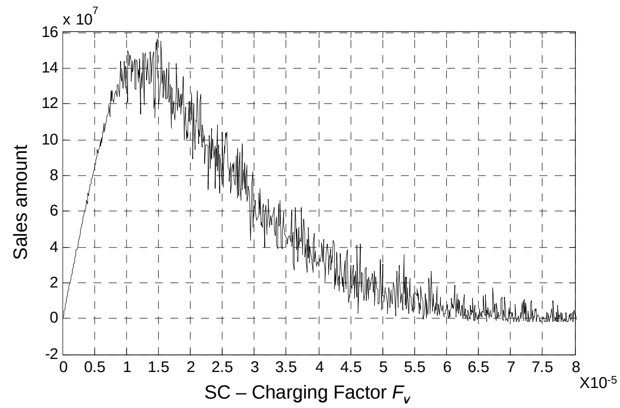

Figure 7 Relation between service charging factor and total sales amount.

A second simulation scenario was carried out to study the QoS level that achieves maximum sales amount in the presence of more than one category of customers. This was done by adding another user category with an acceptable loss rate which ranges between 10^{-20} and 10^{-11}, where the two categories access the service through one service class.

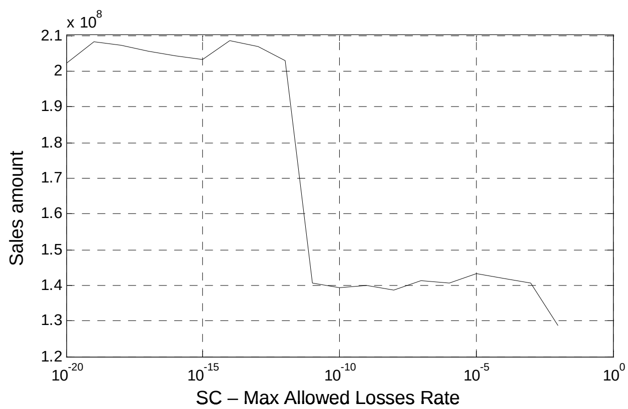

Figure 8 Relation between total capacity and total sales amount.

The results were obtained by performing simulation experiments to calculate the average amount of sales for different QoS points ranging from 10^{-20} to 10^{-1}, as shown in Figure 8.

The curve in Figure 8 shows that the maximum sales value can be achieved when the maximum loss rate is in the range of (10^{-20} to 10^{-11}). Taking into consideration that the two ranges (10^{-5} to 10^{-1}) and (10^{-20} to 10^{-11}), it is apparent that the maximum sales amount occurs within the range of higher QoS level. In this range, the customers of high and low QoS requirements can be fulfilled, although not all customers of the category with lower QoS requirements can afford the price of the service (WTP). On the contrary, at lower QoS range (10^{-5} to 10^{-1}), all the customers with higher QoS requirements cannot be fulfilled. Hence, it is clear that the range of higher QoS attracts more customers, and then achieves more sales amount for the service provider.

VI. CONCLUSION

The efficient utilization of the bandwidth and the optimum price for a service provider applying a QoS based differentiated service classes model to provide services to the customers is presented in this paper. The QoS level of a service was measured in terms of maximum acceptable loss rate in data.

A discrete event simulation technique was implemented to analyze the proposed QoS based differentiated service classes model and determine:

- The optimum guaranteed QoS level for each service class.
- The optimum price for each service class at which the service provider will achieve maximum revenue.
- The optimum total bandwidth required for the service provider.

Then, a mathematical solution was found and the results were compared with a simulation case study.

The service provider was assumed to provide a service to different categories of customers. Each category can have its own specific interarrival time to the service, service duration and a willingness to pay.

Results show that, service classes with a guaranteed QoS level should be in the range of the customers' category of the smallest loss rate, since all the other categories can accept that level. The optimum price of the SC depends on its guaranteed capacity and the users' willingness to pay behavior only, while the total shared bandwidth was affected only by the users' interarrival time and service holding time.

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