FUZZY LOGIC BASED DYNAMIC PRICING SCHEME FOR PROVISION OF QOS IN CELLULAR NETWORKS

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Abstract: Accurate forecasting of demand for cellular services is essential. The high infrastructure implementation costs involved plus overestimation of demand can be very costly. In addition the difference between peak and off-peak demands for wireless services can be very significant, both temporary and spatially. Gearing the network to meet peak demand would result in under-utilised network capacity most of the time. It has been suggested that real-time or dynamic pricing (variation of tariff according to network utilization) could provide an additional strategy for encouraging more efficient use of available resources. The aim of this research work is to investigate the implementation a Fuzzy Logic Controlled Dynamic Pricing (FLCDP) in a simulated cellular network for improved quality of service (QoS). Improvement in revenue collection is also investigated. Simulations were carried out using MATLAB. The results show that the network utilization is improved and an increase in the system availability and reliability: which are the two major parameters for QoS measurement. The revenue collected under FLCDP is greater than under flat rate pricing.

1 INTRODUCTION

The deployment of cellular networks is ever on the increase and accompanying this increase is the user demand for more services and the provision of network QoS. The bandwidth and frequency spectrum for mobile services is critically limited, leaving very little room within which to manoeuvre to provide the demand for more network services and to meet network QoS requirements. To address these limitations, the cellular network service providers need new tools to efficiently and effectively optimize their networks Abiri 2001 and to support QoS schemes in the networks. A number of solutions have been proposed based on cell splitting and frequency re-use Bouroche 2003, dynamic channel allocation or alternative routing Ahmad 1999, and adaptive cell-sizing algorithm. These methods often imply either an increase in system complexity/deployment or a significant degradation of the QoS. The alternative approaches proposed in the literature, Ahmad 1999, Peha 2000, Fitkov-Norris 2000, Hou 2001, Viterbo 2001 and Yaipairoj 2004 are based on dynamic pricing strategy to modify the user demands to fit within the available network resources and thereby provide network QoS.

1.1 Dynamic Pricing Strategy

Currently implemented network services pricing schemes are static, either depending on the time of the day or on defined ON and OFF peak periods. However, a major drawback of the current pricing schemes is their inflexibility and inability to account for network load and status of the network resources to vary the price according to the demand for the network resources. Dynamic pricing strategy aims to set the price for network services as a function status of the network resources. For example, when congestion is experienced in the network due to high demand of network resources, the price goes up and goes down when the demand is low. The price information is made available to the users to decide on whether to pay the current price for the network services. The users are required to value their communication and to decide whether to pay the high price or wait until the price decreases to a value they are willing to pay. The overall effect is a decrease in the number of users, resulting in less demand for network resources and a reduction in congestion being experienced in the network. During low demand for the network resources, the price is reduced to allow more users into the network. Thus, dynamic pricing strategy adjusts the price for the network services taking into account the status of the network resources.

Dynamic pricing has been mainly used to control wired networks supporting Internet-based services Paschalidis 2003, Peha 2000. Techniques for deriving the optimal rates have been proposed, which charge user on the basis of the congestion they cause to the network. Dynamic pricing on cellular networks is a resent research domain. In Fitkov-Norris 2000 a self –regulated system is proposed and the goal of the algorithm is to maximize both the revenue for service provider and the welfare of the users, that is, to choose the pricing function, which offers the best utilization of system capacity whilst keeping the call blocking probability at a desired level. A new dynamic pricing scheme for cellular networks is proposed in Hou 2001. Unlike Fitkov-Norris 2000, Hou 2001 and Hou 2002 introduces the notion of incorporating dynamic pricing and call admission control. In Viterbo 2001 yet another approach to dynamic pricing in mobile networks is presented which is based only on connection oriented services. Another interesting paper is Yaipairoj 2004, gives mobile users alternatives by either accepting the services with higher price based on dynamic pricing scheme or holding on to the conventional scheme (fixed low rate) with acceptable degradation in performance.

In this paper, we propose dynamic pricing strategy for network services which is controlled by a fuzzy logic system. The price charged for the network services varies with the network load or the status of the network resources. The main objectives are to implement a fuzzy logic based dynamic pricing of the network services. Control theories, especially non-linear controllers, has found a wide range of application in cellular networks. Call Admission Control in cellular networks has been controlled using fuzzy logic systems Doru 2004, Mino 2009, Ravichandran 2009 or neural-fuzzy system represented by Zhong 2008. Mobile location estimation has also been implemented using fuzzy logic controller like the work presented by Xuemin 2002. Ravichandran 2009 also introduces a system in which fuzzy logic system can be used to allocate bandwidth in a mobile multimedia network. Therefore, dynamic pricing in cellular networks can also be implemented using controllers. Hence, a control-based dynamic pricing strategy in cellular networks is proposed.

This paper is arranged as follows; section 1 provides an overview of dynamic pricing strategy and the road map of the paper. Section 2, describes the operation of the dynamic pricing scheme, section 3, presents the cellular system modelling. Section 4, describes the controller design of the dynamic pricing strategy, section 5 presents simulation test results and the paper is concluded in section 6.

2 SYSTEM DESCRIPTION

The cellular network system is shown in Figure 1, the status information of the network resources is continuously gathered and is used to set the price $p(k)$ for network services. The calls are generated by the users *A, B* and *C* willing to pay differentiated prices, p_a, p_b, and p_c respectively for the integrated network services. The calls generated pass through call admission control which admits the calls into the cellular network when. p_a, p_b or $p_c < p(k)$.

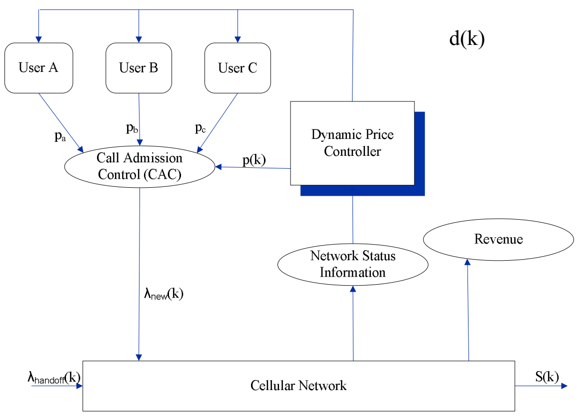

Figure 1: Dynamic pricing system components.

The total number of calls handled by the network is given by:

$$s(k) = f(\lambda_{new}, \lambda_{handoff})$$

where $\lambda_{handoff}$ is handover calls from neighbouring base stations, $s(k)$ is network throughput and λ_{new} is calls admitted by the call admission control. The network throughput $s(k)$ is maintained at a level to ensure optimum utilization of the network resources.

This is achieved by dynamically varying the set price and using the set price to control λ_{new}.

The communication system incorporating dynamic pricing strategy and revenue collection module shown in Figure 1 is also used to collect the cumulative revenue for integrated network services over a fixed period when dynamic pricing strategy is applied and when flat rate pricing strategy is applied.

3 CELLULAR SYSTEM TRAFFIC MODELLING

In this section we mathematically model the communication network traffic presented in Figure 1 A mobile network is a complex system and may not be possible to produce a tractable model of such a system. In this analysis a number of simplifications are made to produce a model that captures essential behaviour of the system. The main assumption made is to ignore all call hand-offs, that is $\lambda_{handoff}$ is assumed to be zero. This is a significant simplification as hand-off calls make up approximately two thirds of the traffic in the used by Hou 2002. However there is no universally agreed hand-off call model because they depend on various parameters (new call entrance rate, hand-off call probability, cell dwell time, call duration) thus, including hand-off calls makes the model significantly more complex. The network throughput is denoted by $s(k)$, whose unit is the maximum number of packets that can be transmitted over the link per unit time.

According to (Bin 2003), the arrival of new voice calls for guaranteed services and new data calls for best-effort services are Poisson distributed with arrival rate $\lambda_g(k)$ and $\lambda_b(k)$ respectively. Hence, the total arrival rate is $\lambda_g(k)+\lambda_b(k)=\lambda(k)$.

In a dynamic priced network, the total arrival rate does not only depend on the time but also on the price for the network service charged at any time k.

In the modelling of the mean arrival rate of the telecommunication system, $\lambda(k)$ is a function of nominal network load, network demand and price. The mean arrival rate is also such that it is zero when there is no demand. This model resulted in;

$$\lambda(k)=\kappa_1 d(k)\{N_0+\kappa_2(P_0-p(k))+\kappa_3(d(k)-D_0)\} \qquad (1)$$

where, $\kappa_1, \kappa_2, \kappa_3$ are constants, $d(k)$ is the dynamic demand (in percentage), D_0 is the nominal demand, P_0 is the nominal price, N_0 is the nominal network load, and $p(k)$ dynamic price.

The number of arrivals in time k is Poisson distributed with probability distribution given by

$$\Pr\{No.of\ call=n\}=\frac{\{\lambda(p(k),d(k),k)\}^n e^{-\lambda k}}{n!}, \quad (n=0,1,2\ldots) \qquad (2)$$

where, Pr is the probability function, $\lambda(p(k),d(k),k)$ is the system call arrival rate, k is time and n is the number of calls.

Call duration was modelled by exponentially distribution represented in equation 3 with a specified departure rate k.

$$\Pr\{No.of\ call=0\}=e^{-\lambda k} \qquad (3)$$

The acceptance of packets is also follows Poisson distribution.

In general, the arrival and traffic modelled by equations (1), (2) and (3) are presented in Figure 2.

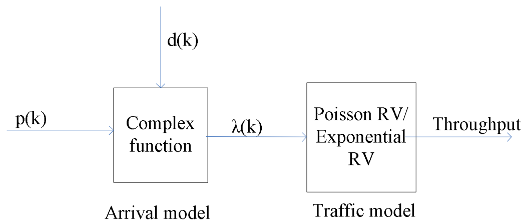

Figure 2: A simple telecommunication network traffic model.

4 CONTROLLER DESIGN

The system utilization (Figure 3) shows that the number of calls in progress/network loads, ranges from 15% to 99% under flat rate pricing. This indicates that the network services are not optimally utilized at all times of the day. In dynamic pricing strategy, we desire that the deviation between the network utilization level and the network optimal level is minimal at all times. In the controller design, we choose a point at which the network service provider wishes to operate (network optimal level). At the chosen point, the network service provider guarantees users satisfaction and the revenue collection results in profit for the service provider. To determine the optimum point for network usage, set points or optimal points from 3000 to 7000 units were investigated.

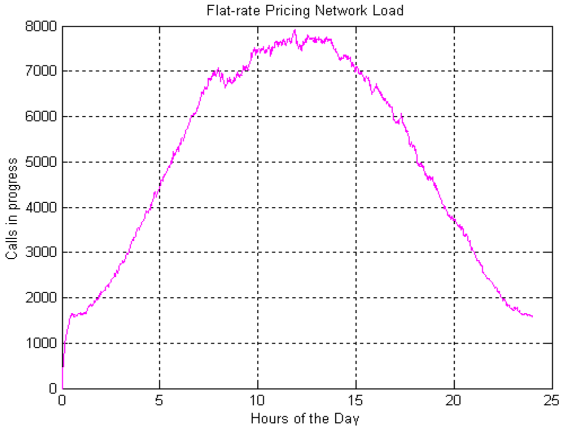

Figure 3: Simulated traffic pattern for flat rate pricing.

The following steps were followed in designing the system:

1. Choose a reference point for the network operator.
2. Determine the parameters for system training, inputs and outputs.
3. Training of the Fuzzy Logic system with the price as the output and error in network load and change of this error as the input.
4. Apply the trained system to dynamically regulate the price depending on the network load.

Three reference points, namely 3000 (40%), 5000 (62%) and 7000 (88%), were chosen. In control theory, for a single input system, there are two inputs to the fuzzy logic system; error (command-feedback) and the error-dot (rate of change in error). For this system, the error represents the difference in reference point and the system throughput, while the error-dot represents the rate of change of this error at any given time. The outputs of each of the fuzzy logic are then used to test the modelled cellular network as represented in Figure 5.23. The system throughput is then feedback for control purposes. Each network throughput is fed back to be compared with the reference point and for further control.

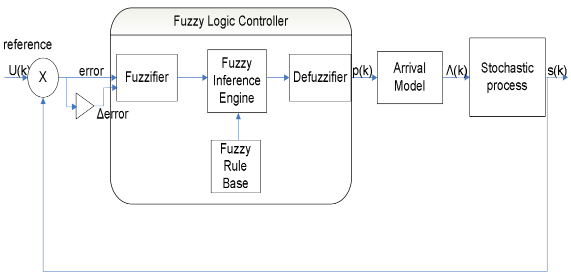

Figure 4: Fuzzy logic-base dynamic pricing.

The modelled fuzzy controlled dynamic pricing scheme shown in Figure 4. The operation of the proposed scheme is divided into two major sections:

- Training section
- Testing section

The training section involves fuzzification of the two inputs, determination of membership functions and the fuzzy inference rules. The following steps were followed in training the system:

1. The fuzzy parameters of error and error-dot were described by the following adjectives: “negative”, “zero” and “positive”. To represent these linguistic variables the following notations were used:
   For error, the following are defined: Negative Error Ne, Zero Error Ze and, Positive Error Pe. For error-dot, the following are defined Negative Error-dot Nd, Zero Error-dot, Zd and Positive Error-dot Pd.
   The output of the system is the service price whose linguistic variables were denoted by Negative Price offset Np, Zero Price offset Zp and Positive Price offset Pp.
2. Determination of the membership functions: To obtain the membership functions, the example given by Kosko 1997 was followed, where both triangles and trapeziums are used to construct the membership function because they are suitable for real-time operation Zadeh 1994. For set point 3000 units, the membership functions of each of the inputs and outputs are given in Figures 5, 6, and 7. The other set points, 5000 and 7000 units had a similar membership function except for the range in the x-axis.

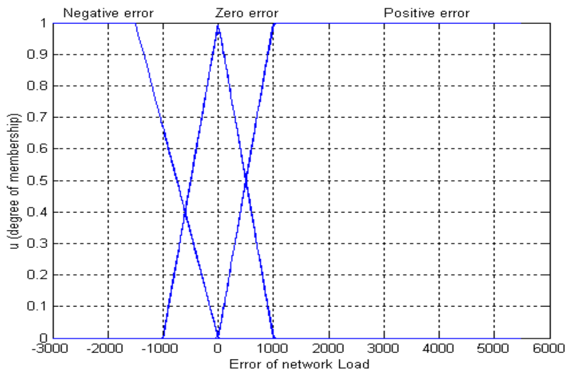

Figure 5: Error membership functions.

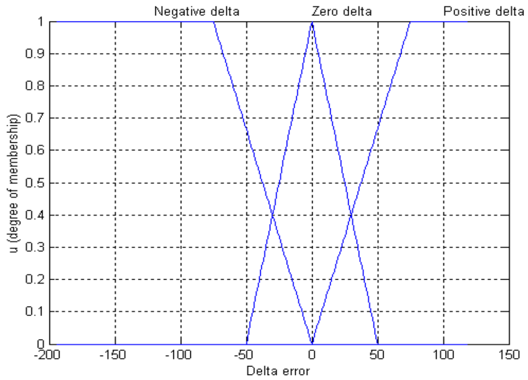

Figure 6: Error-dot membership functions.

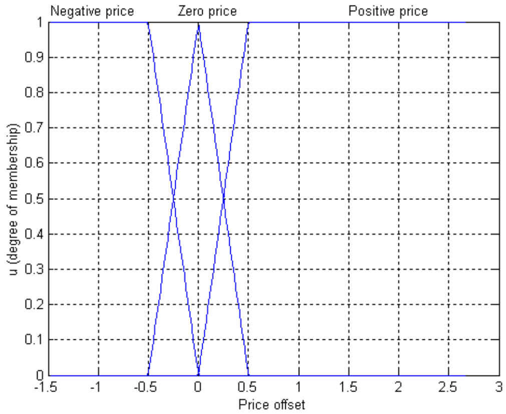

Figure 7: Price offset membership functions.

3. Nine sets of Mamdami type Fuzzy Inference Mamdani 1974 rules are derived for each reference point and every rule presents a fuzzy relation between the inputs (Error and Error-dot) and the output (price) as follows;

If Error = Ne AND Error-dot=Nd, THEN the Priceoffset =Np
If Error = Ze AND Error-dot=Nd, THEN the Priceoffset =Pp
If Error = Pe AND Error-dot=Nd, THEN the Priceoffset =Pp
If Error = Ne AND Error-dot=Zd, THEN the Priceoffset =Np
If Error = Ze AND Error-dot=Zd, THEN the Priceoffset =Zp
If Error = Pe AND Error-dot=Zd, THEN the Priceoffset =Pp
If Error = Ne AND Error-dot=Pd, THEN the Priceoffset =Np
If Error = Ze AND Error-dot=Pd, THEN the Priceoffset =Np
If Error = Pe AND Error-dot=Pd, THEN the Priceoffset =Pp

4. Deffuzification of each of the fuzzy outputs was obtained using the CoG method represented in equation 4.

$$p_1(k), p_2(k), p_3(k) = \frac{\sum_{n=1}^{9} \mu_{\min(Error_n, Error-dot_n)} C_{P_n}}{\sum_{n=1}^{9} \mu_{\min(Error_n, Error-dot_n)}} \tag{4}$$

where $p_n(k)$ is the price for each set point, $\mu_{\min(Error_n, Error-dot_n)}$ is the combined membership value for the two inputs and C_{P_n} is the centroid for the price membership.

5 SIMULATION TEST RESULTS

In this section, we present the results obtained using our analytical model simulated in MATLAB. We ran two simulation tests: the first test (section 5.1) was to investigate how to optimize the usage of the network resources under dynamic pricing and flat pricing schemes. The second test (section 5.2) was to collect the total revenue over a fixed time period when both dynamic pricing and flat pricing schemes are applied and to compare the revenue collected.

5.1 Network Resources Utilization

The calls arrival pattern under flat rate pricing strategy is shown in Figure 8. It can be observed that the utilization of the network is not uniform. At certain times the network is under /over utilized. The network service provider increases the price during peak time and reduces during off-peak.

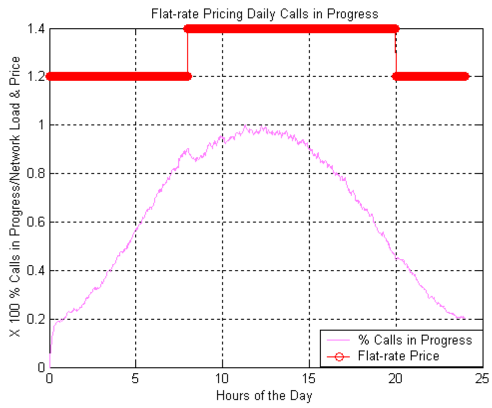

Figure 8: Network Load and Price under Flat Rate Pricing Scheme.

The simulated cellular network under dynamic rate pricing strategy shown in Figure 9 indicate that in the FLCDP system, the network utilization is improved by the reduction in the call arrival rate at overload and reduction of call arrival rate at under load. The reduction at overload decreases with increase in network set point while increment at under-load increases with increase in the network set point.

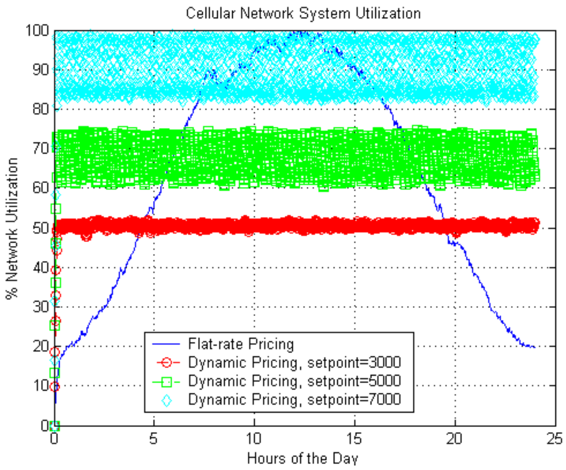

Figure 9: Network Utilization under Dynamic Pricing Scheme.

Figure 10 show that the dynamic price charged for the services depends on the network load shown on Figure 9. The simulation results (Figure 9 and 10) can be used to argue that dynamic pricing can be used to influence the user demand for the services and, the demand influences the availability of the network resources and hence pricing.

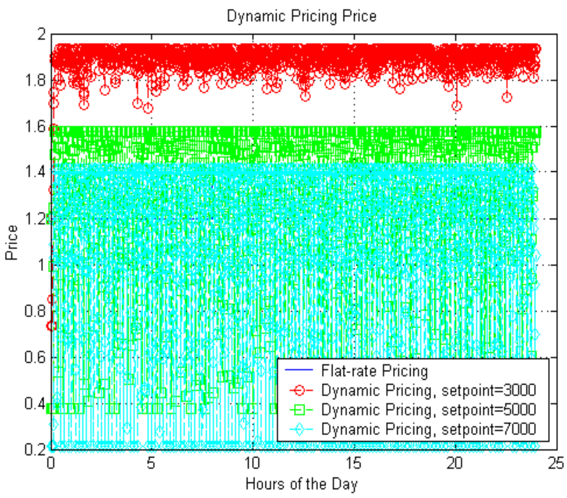

Figure 10: Price Charged under Dynamic Pricing Scheme.

The high price discourages the user from utilizing the network services, freeing the network resources thus, resulting in high network availability. The low the price encourages the user to utilize the network services by admitting more users into the network resulting in high demand for the network resources. Whenever there is an imbalance between the availability of the network resources and the demand for the network services, dynamic pricing can be used to maintain the availability of the network resources at an optimum level as shown in Figure 9.

5.2 Total Revenue Collected for the Network Services

Based on the cellular network system shown in Figure 1, we ran simulation test to collect the total revenue under flat-rate and dynamic pricing schemes for a period of 24 hours. The results obtained are shown in Figure 11. Investigation of the revenue collected was not the objective of the research but an offshoot of the research to find out if there would be any difference in revenue collected under dynamic and flat rate pricing schemes. The revenue collected under FLCDP is greater than that of flat rate pricing and the difference increases with decrease in network set point. The difference in collected revenue for the different set points is due to the fact that at low set point, many users could be willing to pay the set price. While at high set point, very few users could be willing to pay the high set price.

The high revenue collected under dynamic pricing is because Dynamic Pricing Scheme maintains optimal utilization of the network resources thus resulting in more users and more revenue collection. While under flat rate pricing scheme, users are discouraged when the price is high, resulting in non-optimal utilization of network resources and hence low revenue.

Under the dynamic pricing scheme, new users willing to pay the current services price are always being admitted into the network, contrary to the flat rate pricing scheme which blocks users when the network resources are consumed. The resulting cumulative revenue collected is thus higher under dynamic pricing scheme as compared to flat rate pricing scheme.

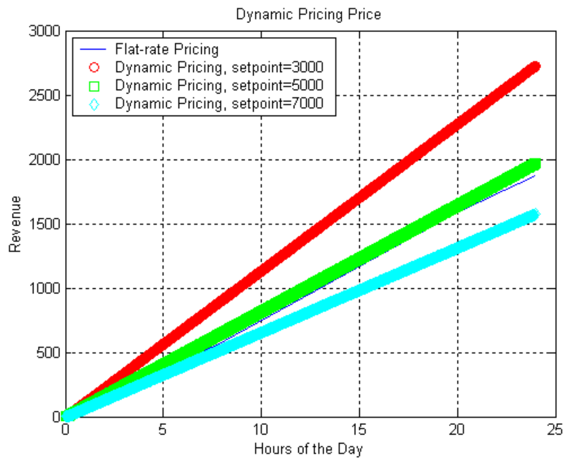

Figure 11: Revenue under Flat-rate and Dynamic Pricing.

Under the dynamic pricing scheme, new users are always being admitted into the network as opposed to the flat rate scheme thus, the resulting cumulative revenue collected is higher in dynamic pricing scheme as compared to flat rate scheme.

6 CONCLUSIONS AND FUTURE WORK

The simulation results in Figure 9 show that an optimal usage of the network resources is achieved under dynamic pricing as compared to flat rate pricing scheme. Regulating the price charged for the network services under dynamic pricing scheme as indicated in Figure 10, provides a mechanism to maintain the status of the network resources at an optimum level. In the flat rate pricing, when congestion (due to scarcity of network resources) is experienced in the network, new calls are blocked or dropped resulting in high blocking probability. While in the dynamic pricing scheme, when congestion is experienced, the network service price is increased thus only the users willing to pay the new network service price will use the network. This results in a lower blocking probability or fewer dropped calls. By dynamically varying the network price, the service provider provides the network services to at a price the users are willing to pay. The resulting better usage of the network resource and the fewer blocked/dropped calls enables the service provider to guarantee the quality of service to the user, as the system ensures system availability and reliability. The results obtained in this research have shown that the fuzzy-based dynamic pricing scheme can be used by the network service provider as a mechanism to support network QoS to the users. When the results in Figure 11 for dynamic and flat rate pricing schemes is compared, it is observed that total cumulative revenue collected is higher under dynamic pricing scheme. The conclusion drawn from these results is that implementing dynamic scheme would result in more revenue for the network service providers if the service provider chooses the optimal operating point appropriately. Dynamic pricing strategy converts congestion, delays and queue costs into monetary values for the service provider.

Future work includes considering that each network service has a unique traffic and how this type of dynamic pricing scheme can be implemented in the real network.

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