Abstract—We propose a novel pricing incentive mechanism based on multi-stages traffic classification methodology supporting load balancing and allocating network resource efficiently for QoS-enabled networks in this paper. We integrate the pricing with QoS routing and present a novel pricing incentive mechanism meeting the QoS requirements of different applications. This mechanism provides an equitable pricing incentive for applications according to their service requests. A novel multi-stages traffic classification methodology that brings together the benefits of port mapping, signature matching and flow character classification techniques is motivated by variety of network activities and their QoS requirements of traffic. We study the pricing and different levels of services in detail and integrate admission control scheme and load balancing in our framework. By theoretical analysis and extensive simulations, we prove its effectiveness in making traffic load balance and providing an incentive for users to utilize network resources to users’ satisfaction.

Index Terms—pricing incentive, QoS-enabled, service level, traffic classification

I. INTRODUCTION

Internet traffic will increase 46% annually from 2007 to 2012 according to measurement study in the literature. The demand for bandwidth management methods that optimize network performance and provide QoS guarantees has increased substantially in recent years. With the next generation networks evolving into a multi-level network, microeconomic principles have been applied to various network resource management issues[1]. Price is such an important economic incentive for the end-users, it is usually considered as an effective mechanism for network management. Pricing schemes are based on QoS level according to different application entail congestion control and load balance. A network supporting multiple classes of service also requires a differentiated pricing mechanism to allocate traffic for different levels of service, rather than relies on flat rate pricing adopted by Internet service providers. Form the user’s perspective, users can choose different level of services according to application request[2]. From the Internet service provider’s perspective, pricing can find the optimal price that maximizes the provider’s revenue or profit and improves the network resources utilization.

Traffic classification is fundamental to solve difficult network services, including traffic modeling, security surveillance, real-time quality of service and provision for future resources[3-4]. A network operator can whether or not classify traffic into different application accurately and directly determines the success of many of the network management tasks above[5]. New applications, for example, peer-to-peer(P2P) networks have become extremely popular for many different applications, such as file sharing, live video streaming, IP-TV, and VoIP services etc.[6]. The ability of dynamically identifying and classifying flows according to their network applications is highly beneficial for estimating the size and capacity demand trends for network planning and making traffic requiring special QoS adaptively[7].

In this paper, in order to efficiently and effectively use network resources, we investigate the issue of integrating pricing into QoS routing and present a pricing incentive mechanism based on multi-stages traffic classification methodology which is more suitable for the future QoS-enabled Internet. In order to achieve flexibility, high accuracy, early detection, low overheads, robustness and high performance for pricing process, we present a novel multi-stages traffic classification methodology with minimum manual intervention to identify all kinds of Internet application. In contrast to previous work in pricing, we assume each network element incorporates a load monitor so that price can be based on its current load level. This pricing strategy will give users the right economic incentive and reflect the current network condition effectively since the prices for non-congested links do not have the significance as the price for congested links[8]. In order to use the network, the users have to purchase all resources along this path. When end-to-end connection is added to a heavy load link, it will cost larger budget than adding to a light load link[9].

The remainder of this paper is organized as follows: Section II reviews some background and related work in this area. In Section III, we discuss the pricing incentive
mechanism and pricing strategy based on multi-stages traffic classification methodology, and identification of all kinds of Internet traffic will also be presented in this section. Section IV gives the experimental comparison of classification methodology. Finally, we conclude our paper and discuss future work in Section V.

II. BACKGROUND AND RELATE WORK

Pricing for the next generation network in general has been an active research area. Several different pricing mechanisms[10-19] have been studied according to the following objectives. The first aim is to design a simple and scalable mechanism, the second goal is to achieve the optimality and economic efficiency of network usage, the last goal is to allow the service providers to supply better QoS guarantee to the customers. Many optimal pricing schemes have been proposed in the past years. In [12], Paris Metro Pricing(PMP) partitions the network into logically separated channels with different prices. It is expected that the higher-priced classes will have less load and will provide better service. In [14], two-tier auctioning mechanisms support DiffServ in a multi-domain environment. In this model, the network is decomposed hierarchically into sub-network and each sub-network is abstracted into a single bottleneck capacity. In [17], a second-price auctioning model is used in the network where each packet carries a bid in its header. The transmitted packets will be charged for the market price rather than the actual bid where the market price is the highest rejected bid. In [18], smart market model provides a priority relative to other users, and is not an absolute promise of service, a packet is admitted if the bid exceeds the current cutoff amount, determined by the marginal congestion costs. In [19], game-theoretic algorithms have been proposed for multi-class QoS provision. In the literature, the most commonly used approach is to create an optimization model and find the optimal price for the use of network resource. But the literature work on networking is restricted to theoretical issues, and the results are not easily applicable to real networks. Our pricing incentive mechanism is a flexible and scalable pricing mechanism in contrast to previous pricing schemes according to multi-stages traffic classification methodology.

The research of traffic classification has maintained continuous interest. The port-based traffic classification relies on well-known port number to classify different Internet application [20]. However, the new P2P applications use different strategies to camouflage their traffic in order to evade detection. So the port-based applications use different strategies to camouflage their Internet application [20]. However, the new P2P relies on well-known port number to classify different continuous interest. The port-based traffic classification signature searching in the payload of every packet traffic or newly P2P applications. On the other hand, payload[21]. Although this solution could achieve high classification method is proposed to inspect the packet transmission of raw dataset. This method can be well suited with Internet traffic classification, as long as the traffic classified into categories that exhibit similar characteristics in parameters. Nguyen et al. [23] provided context and motivation for the application of ML techniques to IP traffic classification, and reviewed some significant works.

III. PRICING INCENTIVE MECHANISM BASED ON MULTI-STAGES TRAFFIC CLASSIFICATION METHODOLOGY

A. Pricing Incentive and QoS Routing

Network pricing has recently been embraced by researchers in the multiservice broadband networks as an economic issue, and covering the infrastructure expenses and operational expenses through charging the end users as a resource management issue. Network users act independently and sometimes “selfishly” without considering the current network traffic condition. If each user requests the resources that maximize one’s individual level of satisfaction, there should have some mechanisms to provide incentives for users to behave in ways that improve overall utilization and performance. One of the most important incentives is the monetary incentive which can raise element price to make some users request fewer resources.

As mentioned above, we present a mechanism integrating pricing incentive into QoS routing as shown in Fig. 1. Based on the requirements of QoS, each router is composed of a cognitive plane and a traditional routing plane. The traditional routing plane is responsible for the transmission of packets. But the most important is a cognitive plane that is responsible for the collection and exchange of the control message such as QoS state, user request, pricing, etc.

As shown in Fig. 1, the traditional routing plane is composed of 3 modules. The packet label module label the every packet level by adding the needed information into the packet header. The packet transmission module handles incoming packets and forwarding packet to output links. The link state exchange module updates each router

![Figure 1. QoS routing mechanism](image-url)
state periodically. All in all, the traditional routing plane implements the basic function of router.

In order to use the network resource efficiently and effectively, this mechanism designs a cognitive plane supporting load balancing. The cognitive plane is divided into 3 modules. The load monitoring module which can send packet trains to probe the network to detect the network service performance. In this way, each network element sets the prices merely based on its own load. The pricing module decides the tariff for each priority class and charges the user’ connection by the measure from the load monitoring module. Price changes very slowly when there are plenty of resources available and increases drastically when the resources become scarce. The routing setup module searches the route obeying QoS requirements for each connection.

B. Multi-stages Traffic Classification Methodology

We propose a novel multi-stages traffic classification methodology which mainly consists of port-based, payload-based and flow character-based stages. In port-based classification phase, traffic is classified into different categories according the port mapping, whereas in payload-based classification phase, the classifier can automatically extracts payload signatures to identify specific protocols, the traffic is categorized into distinct application types. In flow character-based classification phase, we classify Internet traffic by focusing on the characteristics of the traffic through analyzing and constructing empirical model using machine learning.

In this subsection, we describe the design of the multi-stages traffic classification methodology for traffic classification. As illustrated in Fig.2, the overall architecture of multi-stages traffic classification methodology consists of three main phases, namely port-based classification stage, payload-based classification stage and flow character-based classification stage.

The port-based classification aims at classifying the traffic into two broad categories as known traffic and unknown traffic. It would be identified and classified by port mapping. The subsequent payload-based classification can be implemented by automatically extracting payload signatures to identify specific applications. The finally flow character-based traffic classification employing machine learning algorithm to identify different application through constructing empirical model and analyzing flow character.

In flow preprocessing module, the raw packets from network link are captured and packet header information extracted from each raw packet is delivered to flow generator. A flow is defined and identifiable by the 5-tuple (source address, source port, destination address, destination port, transport protocol) [24], with flow termination determined by distinct flow termination semantics, such as FIN/RST[25] or by an assumed timeout. Without being obfuscated by P2P applications, port mapping is the best choice for classifying non-P2P traffic due to its fast and early detection with least overheads compared to other classification methods. The payload traffic classification is used as an assist to port mapping. To deal with traffic in this stage, port-based mapping and payload-based signatures extraction is effective for those fixed port number or signature available P2P and non-P2P applications. In case of detecting the unknown or encrypted P2P application[26], classifiers using machine learning would be used. We will elaborate the port-based traffic classification, the payload traffic classification and the flow character-based classification modules in next part respectively.

Traditional port-based approach has been kept effective to traffic identification for many years since applications tended to abide by well-known port numbers. However, newly emerged P2P applications take measures to avoid detection by camouflaging well-known ports[27]. Thus, port-based traffic identification was reported to be unreliable as early as in 2004. But the report illustrated that port-based classification can identify 30-40% Internet traffic flows. Since non-P2P traffic has excluded flows with the dynamic and masquerade ports, which are incurred mostly by P2P applications, port-based identification is the easy and effective way to accurately classify applications according to application port matching. But this method is no longer valid because of the inaccuracy and incompleteness of its classification results.

Several payload-based analysis techniques have been proposed to inspect the packets payload searching for specific signatures. The payload-based traffic classifier module is comprised of the following functional blocks: payload-based classifier, signature database and signature extractor. Traffic traversing links through this signature matching component where a fast pattern matching algorithm can be classified traffic. The signature extractor can extract signatures for different applications that belong to a particular application class. Fig.3 illustrates the signature extractor is to automatically extract signatures for all kind of applications.

![Figure2. Multi-stages traffic classification system](image)

![Figure3. Payload-base traffic classification approach](image)
assumption that the reverse flow belongs to the same application as the corresponding flow does.

Other alternatives to solve problems of payload-based traffic classification include methods based on the host-behavior that can classify the traffic according to information extracted from the interactions of the end-hosts. At the same time, traffic classification method based on flow statistics shows effective performance in this field. Substantial attention has been invested in data mining techniques and machine learning algorithms using flow features for traffic classification. Machine learning algorithms are generally divided into supervised learning and unsupervised learning.

In this stage, the flow character-based traffic classifier is intended to recognize a particular class in amongst the usual mix of traffic seen on IP networks. Traffic captured in real-time is used to construct flow statistics from which features are determined and then fed into the classification model. Here we presume that the set of features calculated from captured traffic is limited to the optimal feature set determined during training. The classifier’s output indicates which flows are deemed to be members of the class of interest. Certain implementations may optionally allow the model to be updated in real-time. The optimal approach to training a supervised ML algorithm is to provide previously classified examples of every type of IP traffic: traffic matching the class of traffic that one wishes later to identify in the network, and representative traffic of entirely different applications one would expect to see in future.

Prior to the ML modeling, feature selection can be executed offline, regardless of its high complexity. Feature selection is an important step to machine learning which is the process of choosing a subset of original features. It can optimize for higher learning accuracy with lower computational complexity by removing irrelevant and redundant features. We use Sequential Forward Selection (SFS) for optimization based on the observation that supervised ML classifiers. Sequential Forward Selection (SFS) method begins with zero features chosen, sequentially appends one feature that can yield the best classification result to the chosen features. Successively performing this task and finally selecting the combination with the best classification accuracy. This method can produce good results with much less calculation.

Experiment results illustrate multi-stages traffic classification methodology can meet the key criteria, such as low complexity, real time, high accuracy, early detection and robustness to provide QoS guarantees according to all kinds of Internet application levels with minimum manual intervention. This method can learn traffic character from identified known traffic using machine learning, which can help to identify unknown and encrypted applications intelligently and automatically. At the same time, it is practicable and scalable to facilitate online real-time classification on high speed links for large
traffic volumes with low overheads and low computational complexity.

C. Pricing Strategy and Load Balancing

As discussed in Section C, we use the framework of the competitive market model with two kinds of agents: consumers and producers. Consumers seek resources from producers, and producers create or own the resources. The exchange rate of a resource is called its price. Optimal pricing usually requires certain knowledge about user utility or demand to find the optimal price that either maximizes the user utility or provider’s revenue.

In our strategy, we assume that the rarer the resource, the higher the price. It is worth noting that all the prices we mention in this paper are the price per bandwidth unit.

In Fig.6, We define \( l_{base} \) is the base load factor for the network. When the load is lower than \( l_{base} \), the price is at the lower price. When the load exceed \( l_{base} \), the price will be increased rapidly and even dramatically when the load is close to the maximum capacity. We adopted the hyperbolic growth in this condition to reflect our pricing strategy. When the network element is heavily loaded, the price skyrockets and only few users will be willing to accept the price.

We propose a load-based function that determines the bandwidth resource by considering link load state. Let \( P_j(t) \) be the load factor at time \( t \) for service class \( i \) at link \( j \):

\[
P_j(t) = \left( 1 - \frac{1 - l_{base}}{1 - l_j(t)} \right)^n
\]

(1)

Where \( l_j(t) \) denotes the load of service class \( i \) at time \( t \) for a link \( j \). Here \( n \) is a factor used to control the steepness of the curve and \( n>1 \).

Meanwhile, in order to support a wide variety of applications with different service requirement, we design a deterministic service level tariff. In the service level tariff, there are three priority levels, such as High, Medium, Low. Every level owns a certain QoS performance and price, as can be shown in Table1.

Table1 indicates the offered QoS that specifies the QoS parameter by a service provider. Base on the service level classification with QoS, each user is free to choose the priority level and required service guarantee according to the request’s requirement and budget. As shown in Table 1, a connection’s one-way-delay in High level is less 50ms, but in Medium level is less than 200ms. For example, a user request a multi-conference with 2Mbps codec, and choose High level service to transmit data with short delay and low loss rate. The price for this service is 1\( \times \)10\(^{-2} \), but the price in Low level is 1.4\( \times \)10\(^{-4} \).

Now, we can then propose pricing incentive mechanism supporting load balancing. This can be illustrated mathematically. For the ease of understanding, we define \( t \) : the priority of the service

\( j \) : the link that packet traverses

\( b \) : the bandwidth that user requests

\( n \) : the number of links in the path

\( R'_i(t) \) : cost per Mbs at time \( t \) for service class \( i \) at link \( j \)

Having the load-based function (1) and the service level tariff, the price is express by:

\[
C'_i(t) = R'_i(t) \times b \times P_j(t)
\]

(2)

From previous definition, for a particular path in the network, the total price \( C_{total}'(t) \) for traversing the path is the sum of the price across all the links on the path:

\[
C_{total}'(t) = \sum_{j} C'_i(t)
\]

(3)

In order to use the network, the users have purchase all resources along this path. If the link is heavily loaded or users request is High level or the demanded bandwidth is large, a very high price is reasonable. In the next sections, we show demonstrate the admission control and end-to-end pricing to show this pricing scheme is an effective and efficient mean to provide better traffic supporting load for QoS-enabled networks.

D. Pricing and Admission Control

In the literature, most of studies consider the pricing and admission control as two separate management
functions. In the paper, we use price as a primary admission criterion and set the relation between price and admission control. We design a comprehensive end-to-end admission control approach to improve the level of QoS guarantee. The admission control steps are illustrated in the Fig. 7.

![Admission control flowchart](image)

Figure 7. Admission control flowchart

We focus on two underlying aspect: bandwidth and price. The available bandwidth on the selected router must be larger than the requested bandwidth. The bandwidth constraint for a new connection is

$$\sum_{j \in \text{path}} b_j \leq B$$  \hspace{1cm} (4)

Where $B$ is the link bandwidth for the application.

The useful property of our scheme is that our price constraint ensures that the load at link never reach 1. The bandwidth constraint for a new connection is

$$\sum_j R_j(t) \times b \times P_j(t) \leq C$$  \hspace{1cm} (5)

Where $C$ is the user budget for the transmission according the service level tariff.

IV. EXPERIMENTS AND SIMULATION

As illustrated in Fig.8, experimental network were designed to evaluate our multi-stages traffic classification methodology. The architecture includes some hosts running given P2P applications or non-P2P traffic and other applications and some other subnets in the information network research institute. The proposed classifier is put at the gateway of the campus network.

![Multi-stages classification prototype in experimental network](image)

Figure 8. Multi-stages classification prototype in experimental network

We evaluate our multi-stages classification methodology using the campus traffic traces. We collected the link data during three days from 10:00 to 11:00 since June 19 2009. The main applications in our experiments include HTTP, POP3, FTP, PPStream, BitTorrent, eMule, PPlive, eDonkey and Game, etc. The collected data set statistical information can be illustrated in Table 2. Internet traffic classification schemes operate on the notion of network flows. A flow is defined to be as a series of packet exchanges between two hosts, identifiable by the 5-tuple (source address, source port, destination address, destination port, transport protocol), with flow termination determined by an assumed timeout or by distinct flow termination semantics.

<table>
<thead>
<tr>
<th>Type of flow</th>
<th>Application</th>
<th>Num of flow</th>
<th>Percent(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>WWW</td>
<td>Http</td>
<td>345028</td>
<td>34.72</td>
</tr>
<tr>
<td>FTP</td>
<td>Ftp</td>
<td>88841</td>
<td>8.94</td>
</tr>
<tr>
<td>MAIL</td>
<td>Smtp Pop3</td>
<td>32595</td>
<td>3.28</td>
</tr>
<tr>
<td></td>
<td>Bittorrent</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>eDonkey</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>eMule</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>PPStream</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>PPlive</td>
<td></td>
<td></td>
</tr>
<tr>
<td>DATABASE</td>
<td>Oracle</td>
<td>7254</td>
<td>0.73</td>
</tr>
<tr>
<td>GAME</td>
<td>Wow</td>
<td>64495</td>
<td>6.49</td>
</tr>
<tr>
<td>INT</td>
<td>Telnet SSH</td>
<td>198</td>
<td>0.02</td>
</tr>
<tr>
<td>TOTAL</td>
<td></td>
<td>993745</td>
<td>100</td>
</tr>
</tbody>
</table>

In preprocessing module, packets are aggregated into flows by 5-tuple, then statistics of the first $p$ packets of each flow are calculated according to the selected feature set $S=\{\text{flow duration, source port, destination port, total packets of flow, total bytes of flow, packets inter-arrival, packet payload, packet length}\}$. Thus the dataset is formed and stored for training.

The performance of classification can be measured by the accuracy and computational complexity. A key criterion on which to differentiate between classification techniques is predictive accuracy. To measure the performance of our proposed method, we use three metrics: accuracy, precision and recall. In this paper, $TP$, $FP$, and $FN$ are the numbers of true positives, false positives, and false negatives, respectively. True Positives is the number of correctly classified flows, False Positives is the number of flows falsely ascribed to a given application, and False Negatives is the number of flows from a given application that are falsely labeled as another application.

A good traffic classifier aims to minimizing the FN and FP. Some works make use of accuracy as an evaluation metric. It is generally defined as the percentage of correctly classified instances among the total number of instances.

$$\text{Accuracy} = \frac{TP}{TP + FP}$$  \hspace{1cm} (6)

The overall effectiveness of the classifiers is measured by the overall accuracy.
behavior and connection statistical feature. P2P applications share the similar characteristics of flow enough to identify P2P traffic based on the fact that the with considerable accuracy. The methodology is robust that our methodology can identify unknown P2P traffic unknown P2P traffic is shown in Fig.6, which indicates classification accuracy using the test set with or without capability of detecting unknown P2P traffic. The average test set to 2000 flows in order to demonstrate the

time, one of the k subsets is used as the test set and the other k-1 subsets form the training set. Performance statistics are calculated across all k trials. This provides a good indication of how well the classifier will perform on unseen data.

P2P traffic monitoring and control have attracted an increasing amount of interest in the past few years. P2P traffic classification is the most challenging problem in Internet traffic classification, whereas most flow prioritization, traffic shaping and QoS differentiation are pertinent to P2P traffic. The goal of this part is to verify whether the proposed multi-stages classification methodology that is robust or flexible enough to detect the unknown and encrypted P2P traffic.

We devise the experiment scheme that each of training and test sets is comprised of 20,000 flows. We remove the instances of one type of P2P application (PPStream) from the training set, and let the test dataset include the traffic of specific P2P application. Since the selected P2P traffic has not been trained, it can be simulated as unknown or newly emerged P2P application.

We deliberately increase the PPStream’s share in the test set to 2000 flows in order to demonstrate the capability of detecting unknown P2P traffic. The average classification accuracy using the test set with or without unknown P2P traffic is shown in Fig.6, which indicates that our methodology can identify unknown P2P traffic with considerable accuracy. The methodology is robust enough to identify P2P traffic based on the fact that the P2P applications share the similar characteristics of flow behavior and connection statistical feature.

![Figure 9. Known and unknown P2P traffic identification](image)

The experimental result shows that multi-stages classification methodology could achieve high accuracy with low cost in distinguishing P2P traffic at the beginning of each flow in Fig.9. Another key advantage is the ability to accommodate both known and unknown P2P flows, and identify encrypted P2P traffic. Thus, our scheme would be a promising candidate to deal with P2P traffic identification for the network uses and as the basis of further traffic classification. Therefore, this approach could classify unknown P2P traffic as well as known P2P traffic successfully.

We compare classification accuracy of multi-stages traffic classification methodology with the other classification approaches solely based on port-based approach, payload-based and flow character-based using machine learning Table 3. For the multi-stages traffic classification methodology, port-based approach separates known traffic from the rest of the traffic by exploiting the port protocols in the first stage, the classification overall accuracy is 68.7%, 35.8% for non-P2P and P2P application respectively. In the second stage, it automatically extracts payload signatures to identify specific protocols, the classification overall accuracy is 54.9%, 65.1% for non-P2P and P2P application respectively. In the third stage, the relationship between the class of traffic and its observed statistical properties has been noted. We construct empirical classifier model to classify Internet traffic by focusing on the characteristics of the traffic using C4.5 algorithm, we get 97.9% and 94.6% for non-P2P and P2P application respectively using C4.5 algorithm. Compared with the other classification approaches, the multi-stages classification methodology proposed in the paper can achieve higher overall accuracy.

| TABLE 3 OVERALL ACCURACY OF THE MULTI-STAGES CLASSIFICATION IN EVERY STAGES |
|-----------------|----------|-----|-----|-----|----------|
| Stage           | Traffic  | TP(%)| FP(%)| Overall accuracy(%) |
| First stage     | P2P      | 84.37| 33.02| 49.87 |
|                 | Non-P2P  | 96.58| 1.65 |           |
| Second stage    | P2P      | 90.83| 23.07| 78.46 |
|                 | Non-P2P  | 88.29| 9.12 |           |
| Third stage     | P2P      | 93.91| 4.58 | 95.63 |
|                 | Non-P2P  | 97.65| 3.41 |           |

We calculate the relative computational time, demanded memory and accuracy through the experiments according to different approaches. The performance for different approaches is demonstrated in Table 4. We can find that the multi-stages classification methodology is able to greatly improve the accuracy, while only minimally impacting computational time and demanded memory.

| TABLE 4 PERFORMANCE FOR DIFFERENT APPROACHES |
|-----------------|----------|-----|-----|-----|-----|-----|-----|
| Performance     | Port-based| Payload-based| Character-based| Multi-stages |
| Time(s)         | 0.930    | 4.356 | 1.059 | 3.563 |
| Memory(M)       | 5.976    | 18.407| 5.012 | 10.342 |
| Accuracy(%)     | 49.87    | 49.35 | 67.84 | 96.7  |

In order to illustrate the advantage of multi-stages traffic classification proposed in the paper, we compare different traffic classification scheme from several edges. Table 5 illustrates the distinct advantage of multi-stages traffic classification methodology than other approaches.
In the next part, we describe our simulation model for pricing incentive mechanism based on multi-stages traffic classification methodology. In order to study the behavior of our pricing strategy, we use the ns-2 simulator to simulate one network topology, shown in Fig. 10. The topology contains 8 nodes. All links are full duplex and point-to-point with 3 priority service levels. The capacity of each link is set to 100Mbs. User requests are generated according to a Poisson arrival process. The mean duration of a connection is equal to 50 seconds. The mean duration is exponentially distributed and varied from 500sec to 1200sec. The average required bandwidth of each connection is 5Mbps. We compare the performance between the pricing incentive mechanism supporting load balancing (PASLB) and pricing mechanism (PA) from various angles.

![Figure 10. Simulation network topology](image)

Table 5: Comparison of multi-stages, port-based, payload-based and flow character-based approach

<table>
<thead>
<tr>
<th>Approach</th>
<th>Port-based</th>
<th>Payload-based</th>
<th>Character-based</th>
<th>Multi-stages</th>
</tr>
</thead>
<tbody>
<tr>
<td>Port info</td>
<td>Yes</td>
<td>No</td>
<td>some</td>
<td>Yes</td>
</tr>
<tr>
<td>Application signature</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>Identify</td>
<td>Some</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Identify encrypted</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Identify unknown p2p</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Accuracy</td>
<td>Low</td>
<td>mediate</td>
<td>mediate</td>
<td>High</td>
</tr>
<tr>
<td>Expansibility</td>
<td>Low</td>
<td>Mediate</td>
<td>High</td>
<td>High</td>
</tr>
<tr>
<td>Online learning</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
</tr>
</tbody>
</table>

In our simulation, the goal is to price the network resource according to the traffic load using pricing incentive and admission control. Hence, we mainly concentrate on metrics such as load distinctness, loss rate, connection failure rate.

![Figure 11. Load distinctness between PASLB and PA](image)

Fig. 11 illustrates how the PASLB behaves given a certain offered load. We compare load distinctness between link(R1,R2) and link(R1,R3) by adopting the PASLB and PA. The result explains that PASLB is much more balancing on traffic than PA. The pricing make price increase and confine the lower level service to choose other link.

![Figure 12. Connection failure rate of PASLB and PA](image)

Fig. 12 respectively depicts the connection failure rate for PASLB and PA. PASLB behaves much better than PA for admitting more connection. The PASLB regulate connection number efficiently by admission control. The result reveals the higher connection rate using pricing as an effective traffic management mechanism.

V. CONCLUSION

Recently, P2P application and Video Streaming have significantly increased their presence in the Internet. This is a challenge for network operators who have to deal with the management of the network resources. From the QoS perspective, accurate traffic classification helps to identify the application utilizing network resources, and facilitate the instrumentation of QoS for different applications. We propose a novel pricing incentive mechanism based on multi-stages traffic classification methodology and allocating network resource efficiently for QoS-enabled networks. The proposed multi-stages traffic classification methodology can identify all kinds of Internet traffic applications using port-based approach, payload-based approach and flow character-based approach with high accuracy, low overheads and robustness. We have also described our pricing scheme and adopted a market-based approach that uses price to balance the traffic load for service differentiation according to the traffic classification and QoS guarantee. The simulation results show that our pricing incentive scheme is indeed defective in terms of providing the right economic incentives to the users and maintaining a certain level of traffic load. However, pricing incentive mechanism for QoS-enabled network in the presence of competition or alternative path remains an interesting open issue.

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REFERENCES


[13] Constantinou F, Mavrommatitis P. “Identifying known and unknown peer-to-peer traffic”. In IFIP NCA’06 Conference.


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