A New Predictive Dynamic Priority Scheduling in EPONs

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Abstract

Efficient uplink scheduling in Ethernet passive optical networks is very important to maximizing the network capacity while maintaining the required quality of service (QoS). Several variants of dynamic bandwidth resource allocation have been proposed in recent research literature. However, the available techniques do not fully exploit the elastic properties of the user traffic. In this paper, we explore optimal predictive resource allocation strategies by exploiting the elasticity of QoS constrained traffic and using the knowledge of traffic patterns of different service classes. We propose a predictive dynamic uplink bandwidth allocation scheme that offers lesser access delay and packet loss rate, yet achieving a higher overall network throughput. We formulate a model for determining the traffic burstiness dependent optimum prediction order that would enhance the quality of prediction with a minimum possible prediction-related processing overhead. We then demonstrate that, in a multi-class access scheduling, with respect to the conventional dynamic allocation strategies, our priority scheduling with judicious prediction of individual traffic classes can enhance the system performance significantly. Our analytic observations are supported by extensive simulation results.

Keywords: broadband access; EPON uplink scheduling; user traffic prediction; priority scheduling; quality of prediction

1. Introduction and Motivation

Access networks are cost-sensitive. Therefore, simple and easily upgradeable technologies are appealing from deployment and maintenance viewpoints. Passive optical network (PON) technology is an attractive contender for the last mile communication or broadband access, as it offers a highly stable broadband communication channel and has the unique feature of easy upgradability that can be done by only changing the electronics at the extreme ends of the networks.

In PON based access techniques, the uplink traffic from different end users are aggregated at the optical network unit (ONU), which is located at the customer site and is capable of buffering the aggregated data. The ONUs are

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connected to passive optical combiner/splitter, which in turn connects to the optical line terminal (OLT) via a single optical fiber. In Ethernet PONs (EPONs), the data packets are encapsulated in Ethernet frames. Because of its compatibility with the ubiquitous IEEE 802.3 Ethernet standards, advantages of low cost, simplicity of maintenance, large coverage area, and multicast and broadcast capabilities, EPON has emerged as a promising broadband access solution.

In EPONs, the downstream data transmission to multiple ONUs is simply broadcast based, wherein the data packets for all ONUs are sent in all downstream links from the passive optical splitter that acts as a hub. An ONU extracts its intended data and delivers to its local users. In the upstream direction, an EPON acts as a multipoint-to-point network. From the optical combiner to the OLT link, the ONUs share a common upstream channel, and at most one ONU may transmit packets to the OLT in a particular time slot. Thus, in the upstream direction, using the shared channel fairly and efficiently is an important media access control issue. To this end, EPON uses time-division multiplexing (TDM) technique and also supports differentiated quality-of-service (QoS) traffic. Particularly, according to the DiffServ model, the user traffic is classified into three. The most delay sensitive traffic with a certain degree of loss tolerance, which requires a guaranteed channel bandwidth, e.g., packetized voice traffic, is classified as expedited forwarding (EF) traffic. The traffic with a more delay flexibility but requiring a minimum bandwidth guarantee, e.g., video, is categorized as assured forwarding (AF) traffic. The traffic with neither delay nor bandwidth guarantee constraints is classified as best effort (BE) traffic.

A multipoint-to-point EPON architecture with *differentiated class based queues at the ONUs* is depicted in Fig. 1, where each ONU collates the class based traffic information and sends it to the OLT for resource allocation. This classification at the ONUs helps the OLT assign the share of total available uplink resource proportionally to the ONUs per service class. In time division multiplex based upstream resource sharing in EPONs, the resource (i.e., number

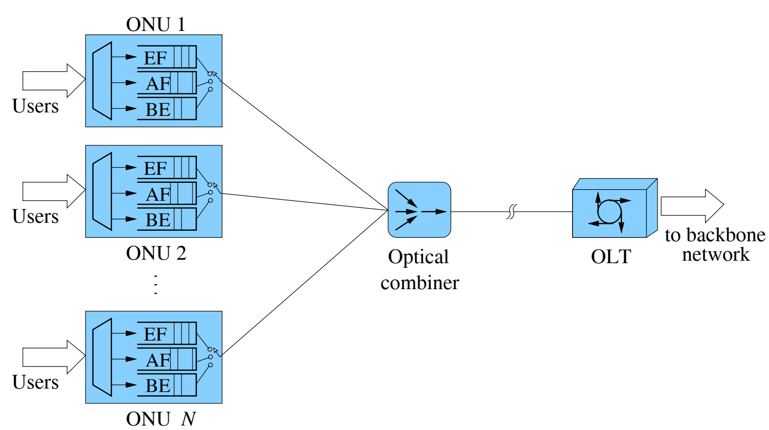

Figure 1: The EPON architecture with differentiated service classes.

of time slots) to be assigned in a frame to different ONUs are done by OLT that takes into account the upstream requests obtained in the previous frame. The efficiency of resource allocation in terms of guaranteeing user QoS and maximizing the system capacity (and hence service provider's revenue) depends on the intelligence incorporated in generating bandwidth requests at the ONUs as well as the bandwidth allocation policy at the OLT subject to the ONU requests.

In recent years, several works have been reported on resource provisioning and differentiated QoS issues, for example, dynamic resource allocation [1, 2, 3, 4, 5], strict QoS support [6], and predictive resource allocation [7, 8]. However, we argue that, fine-tuning the ONU requests and the OLT's allocation strategies can significantly reduce over-provisioning of limited bandwidth resource, which is a key parameter in access networks in view of its cost-sensitivity. Additionally, although the Internet traffic prediction quality was studied [9, 10] and the concept was applied in EPONs [8] earlier, studies on user-end traffic burstiness dependent predictive bandwidth allocation has not been reported in the literature.

In this paper, we address joint optimization of user QoS and system capacity by accounting for the class-based traffic burstiness characteristics. In our proposed predictive dynamic priority scheduling (PDPS), we first show that, even with a naive prediction mechanism at the ONUs, properly utilizing the excess bandwidth of QoS constrained users improves all users' QoS and also enables to achieve an overall higher system throughput. We then show that, by introducing traffic class based prediction mechanisms at the ONUs, the system performance can be further improved in terms of increased total throughput and reduced access delay of different classes. As an example, our simulations show that, compared to a naive first order prediction, with optimum predictors for different traffic classes up to 14% delay reduction of video traffic can be observed at a 91% system load with an equal distribution of voice, video, and data traffic. Also, up to 20% reduction of data packet delay can be observed with optimum predictors, irrespective of the traffic ratio and system load.

The rest of the paper is organized as follows. Section 2 contains a brief survey on the research literature pertaining to our current work. In Section 3, the generic approach of our proposed predictive dynamic priority scheduling is presented. The analysis on our proposed traffic-aware predictions is provided in Section 4. In Section 5, first, numerical results on the impact of traffic burstiness aware prediction on user QoS support and system capacity are discussed, and then the simulation results on multi-class traffic access performance are described. Section 6 concludes the paper.

2. Related Work

Traffic classification and shared upstream resource provisioning issues in EPONs have been addressed independently as well as jointly in prior studies. In TDMA based fixed (static) bandwidth allocation (FBA) [11], resource sharing was based on ONU demands – not based on traffic classes or their temporal dynamics, where the allocated bandwidth by the OLT to the ONU$_i$ is $b_i^g = B_i$. B_i is a constant, which could be different for different ONUs. The inflexibility and hence bandwidth resource waste in static allocation policy was relaxed in several variants of dynamic allocation strategies (e.g., [12, 1, 6, 2, 7, 3, 4, 5]). Interleaved polling with adaptive cycle time (IPACT) [12] considered ONU demands based dynamic allocation, where the OLT adjusts the polling sequence of the ONUs depending on their respective queue lengths.

Traffic class based priority scheduling was combined with IPACT in [1] to meet the delay and jitter guarantees. In bandwidth guaranteed polling approach [2], the ONUs are assumed of two priority classes, and upstream polling sequence is adjusted by the OLT depending on the ratio of active ONUs of the two types. To achieve low access latency, queue length estimation based bandwidth allocation was proposed in [7]. The common feature in [1] and [7] is limited bandwidth allocation (LBA) based on service level agreement (SLA), where the OLT assigns the requested bandwidth to ONU_i in the current frame if the request is less than the SLA_i, or else it grants only SLA_i. The upper limit of bandwidth to be allocated being pre-decided by the respective SLAs, and the total user demand generally being at most the total available bandwidth, in LBA the excess bandwidth per frame remains unutilized. The LBA was further enhanced in [3, 13], called excess bandwidth reallocation (EBR), to dynamically assign the bandwidth in excess of SLA guarantees to the heavily loaded ONUs proportionally to their excess demands.

Explicit differentiated QoS support [14] was studied for the Internet applications to address traffic class specific data loss and delay, where the traffic was categorized into DiffServ model specified three classes, namely, EF, AF, and BE. For explicit QoS guarantee, the dynamic bandwidth allocation (DBA) strategy in [6] assigns a fixed bandwidth to the EF (voice packet) traffic, irrespective of the immediate requirements, which, while maintaining the delay and loss bounds, may invite resource waste. The leftover bandwidth is allocated to the AF (video) traffic first and then to the BE (data) traffic. This approach may lead to the possibility of unused bandwidth by the EF traffic and bandwidth hogging by the AF traffic, causing poor performance of the BE traffic. The paper however did not present any performance results showing the relative performance of different priority classes. The strategy proposed in [4] limits the allocation to EF and AF traffic to their respective SLAs, while assigning the remaining bandwidth to BE traffic. In this approach the AF performance may suffer, even if the assigned bandwidth to the BE traffic remains unused. To achieve fairness among all classes, the bandwidth allocation in [5] is done in three stages: first allocate proportional to the queue length of all classes, then prune the allocated resource if it exceeds the respective SLA-high or SLA-low, and finally allocate the excess bandwidth proportionally to all queues. This approach however does not guarantee strict priority to different classes.

The use of traffic prediction in bandwidth request has been proposed in a few recent studies [4, 8, 15]. To improve loss and delay performance in DBA [3], a linear prediction was proposed in [4] to estimate the new arrivals during the waiting time up to the next allocation cycle at the ONU. The estimated traffic during this waiting period is proportional to the respective SLAs. A two-stage bandwidth request scheme was proposed in [15], where, in the first stage, DBA is performed for the next cycle at the ONU level with the ONUs having more unstable traffic assigned the bandwidth resource earlier – to reduce the prediction error by shortening their waiting times. In the next stage, a linear prediction based excess bandwidth request is done, which is a heuristic modification of the approach in [4], and is a function of the stability degree of ONU traffic. At the OLT, the out of the proportionally available bandwidth for an ONU, the allocations to EF, AF, and BE traffic are done strictly based on their respective requests in order of priority. This process of bandwidth grant is close to the DBA approach in [6], and it could lead to bandwidth hogging by AF as well as EF traffic.

The effect of long range dependence of Internet traffic on the prediction quality was studied in [9, 10]. For the user-end traffic prediction, the approach for EPONs in [4] was further enhanced in [8], where, to factor in the traffic burstiness in prediction a linear mean square (LMS) predictor [16] was used. In this approach, based on the observation in [10], the number of taps in the predictor was chosen 4, which is irrespective of the degree of burstiness a traffic.

While the prior works have advanced the upstream resource allocation in EPONs to a great extent, we observe that, individual traffic class dependent prediction at the ONUs and allocation at the OLT could improve the individual QoS support as well as overall system throughput significantly. In this work, to improve upon fairness and efficiency of bandwidth usage, we extend the LMS prediction approach in [8] for multi-class traffic and modify the DBA algorithms in [6, 5]. Particularly, we demonstrate the importance of burstiness dependent optimal prediction order on the user-level performance as well as system capacity.

3. Generic Predictive Dynamic Priority Scheduling Approach

In our proposed basic predictive approach to bandwidth request and grant, following the DiffServ model, user traffic at the ONUs are classified into three: priority-0 (P0), priority-1 (P1), and priority-2 (P2). P0 is delay constrained, e.g., packetized voice, P1 is more delay tolerant but less loss tolerant, e.g., video streaming, and P2 is delay tolerant but loss sensitive, e.g., data traffic. Using these three classes also allow easy mapping of DiffServ specified EF, AF, and BE classes into 802.1D classes. Instead of per ONU allocation, here the OLT assigns bandwidth with inputs from individual priority queues.

The ONU system model of our proposed priority scheduling is shown in Fig. 2. At the i-th ONU, as the packets

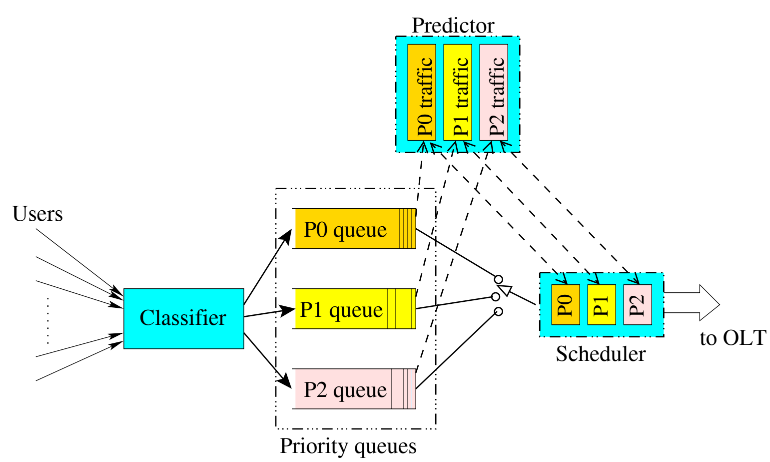

Figure 2: ONU system model with service differentiated predictive scheduling.

of different classes arrive, the uplink frame n carries bandwidth request of each priority class for the service interval

$n+1$ (i.e., frame $n+1$). In doing so, the predictor of each class estimates the traffic arrival during the service interval of a frame. To predict the incoming traffic until the next cycle, a linear predictor is adopted [16, 8] as:

$$\tilde{b}^{w}_{P_{c,i}}(n+1) = \sum_{j=0}^{L-1} \alpha_{P_{c,i,j}}(n) b^{w}_{P_{c,i}}(n-j), \tag{1}$$

where $c \in \{0,1,2\}$, i is the ONU index, L is the prediction order, and $\alpha_{P_{c,i,j}}$ is the weight factor indicating the effect of the actual bandwidth requirement $b^{w}_{P_{c,i}}(n-j)$ for class c at the ONU$_i$ in frame $(n-j)$. The weight factor is updated by the standard LMS (least mean square) algorithm as: $\alpha_{P_{c,i,j}}(n+1) = \alpha_{P_{c,i,j}}(n) + \mu_{P_{c,i,j}}(n) \frac{e_{P_{c,i}}(n)}{b^{w}_{P_{c,i}}(n)}$, where $e_{P_{c,i}}(n)$ is the prediction error in the service cycle n, defined as: $e_{P_{c,i}}(n) = b^{w}_{P_{c,i}}(n) - \tilde{b}^{w}_{P_{c,i}}(n)$, and $\mu_{P_{c,i,j}}(n)$ is defined as $\mu_{P_{c,i,j}}(n) = \frac{L}{\sum_{j=0}^{L-1}\left[b^{w}_{P_{c,i}}(n-j)\right]^2}$.

With the predicted traffic, the requested bandwidth for class c traffic from the ONU $_i$ in the service interval $n+1$ is:

$$b^{r}_{P_{c,i}}(n+1) = b^{q}_{P_{c,i}}(n) + \tilde{b}^{w}_{P_{c,i}}(n), \tag{2}$$

where $b^{q}_{P_{c,i}}(n)$ is the enqueued class c traffic at the ONU$_i$ in n^{th} service interval.

With the ONU requests for the next cycle arrived, the OLT processes class-based bandwidth assignments and informs the ONUs via the subsequent downlink frame. The OLT system model for priority scheduling is pictorially shown in Fig. 3. The assigned bandwidth to the ONUs is governed by the rules as defined below, where the SLA of

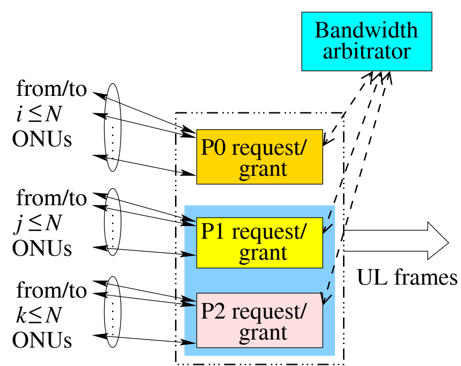

Figure 3: OLT system model for priority scheduling.

class c traffic in ONU$_i$ is denoted by $B_{P_{c,i}}$ and the total bandwidth available for uplink user data traffic is B_{max}. It is assumed, the call admission control ensures that the sum of SLAs of accepted sessions do not exceed B_{max}.

Since the P0 traffic has strict delay constraint, the granted bandwidth for the cycle $n+1$ is given as:

$$b^{g}_{P_{0,i}}(n+1) = \min\left\{b^{r}_{P_{0,i}}(n+1),\ B_{P_{0,i}}\right\}. \tag{3}$$

Subsequently, the bandwidth to the P1 traffic is granted in two phases. In phase I,

$$b^g_{P_{1,i}}(n+1)\Big|_I = \begin{cases} b^r_{P_{1,i}} & \text{if } b^r_{P_{1,i}} \leq B_{P_{1,i}}, \\ B_{P_{1,i}} & \text{else,} \end{cases} \tag{4}$$

Next, the excess bandwidth $b_{ex}(n+1)$ is computed as:

$$b_{ex}(n) = B_{max} - \sum_{i=1}^{N} \left(b^g_{P_{0,i}}(n) + b^g_{P_{1,i}}(n)\Big|_I \right), \tag{5}$$

where N is the total number of ONUs assigned to the OLT. The granted bandwidth to P1 in phase II is:

$$b^g_{P_{1,i}}(n+1)\Big|_{II} = \begin{cases} b^r_{P_{1,i}} & \text{if } b^r_{P_{1,i}} \leq B_{P_{1,i}}, \\ B_{P_{1,i}} + \frac{b_{ex}\cdot b^r_{P_{1,i}}}{\sum_{i=1}^{N}\left(b^r_{P_{1,i}}+b^r_{P_{2,i}}\right)} & \text{else,} \end{cases} \tag{6}$$

and the granted bandwidth to P2 traffic is:

$$b^g_{P_{2,i}}(n+1) = \min\left\{ b^r_{P_{2,i}},\ \frac{b_{ex}\cdot b^r_{P_{2,i}}}{\sum_{i=1}^{N}\left(b^r_{P_{1,i}}+b^r_{P_{2,i}}\right)} \right\}. \tag{7}$$

Note that, the SLA aware allocation to P0 class, as in (3), minimizes resource waste in case some ONUs require less bandwidth than their respective SLAs for P0 class in a cycle. Because P0 is loss tolerant, our proportional excess bandwidth allocation does not account for the burstiness of P0 traffic, and thus P0 queue is served independent of P1 and P2 queues. The assignment in (4) first ensures the minimum resource guarantee to the P1 traffic. Since P1 is also expected to be more bursty, remaining bandwidth allocation is done as per the rule in (6) to the ones those require higher than the P1 SLA. Our excess bandwidth allocation approach, after ensuring the minimum QoS guarantee to P1, also ensures some resource sharing fairness to the P2 traffic.

It can be further observed that, as in [5], our generic resource allocation approach can also be adapted to guarantee a lower bound and an upper bound of QoS for P1 traffic, while addressing some fairness to P2 class.

In our performance studies in Section 5, for all priority class assignments, in general, packets are assumed enqueued if they are not served in the a service cycle, and accordingly the delay of each class and network throughput performance were studied. In case of P0 traffic, the loss rate was also studied with an imposed maximum access delay limit per packet.

4. Analysis of Quality of Prediction

The generic PDPS approach does not address traffic class specific burstiness in determining the predicted traffic. However, this is important to choose an *optimum number of taps* in a predictor, so as to maximize the use of historical information in improving the quality of prediction while maintaining the processing overhead at a minimum. In the following, the effect of prediction order of the LMS filter for different traffic classes on the quality of prediction are analyzed.

To quantify the effect of traffic burstiness on the optimum number of taps, we consider a single class of traffic. As a general user-end uplink traffic pattern, the arrival process is modeled as Pareto distributed [17] to incorporate the property of burstiness and long range dependence. [1] The Pareto distribution can be described as:

$$\Pr[T \geq t] = \frac{\beta^{\alpha}}{(\beta + t)^{\alpha}},$$

where $\alpha,\ \beta > 0$. The burstiness property of a traffic is represented by the Hurst parameter H, which is given by $H = \frac{(3-\alpha)}{2}$. A lower α denotes more bursty traffic, and vice versa. The range of specific interest for self-similarity is $1 < \alpha < 2$, wherein the value of the Hurst parameter is between 0.5 and 1.

The power spectrum of packet counts $S(f)$ for Pareto distributed arrivals can be represented as [17]:

$$S(f) = \begin{cases} f^{-\alpha}, & 0 < \alpha < 1 \\ f^{\alpha-2}, & 1 < \alpha < 2 \\ \text{constant}, & \alpha > 2. \end{cases} \tag{8}$$

Correspondingly, the autocorrelation function can be calculated by taking inverse Fourier transform of the power spectral density:

$$r(t) = \int_{-\pi}^{\pi} S(f) e^{2\pi j f t} df. \tag{9}$$

Considering $1 < \alpha < 2$ and substituting the value of $S(f)$ from (8) we have,

$$r(t) = \left(\frac{-1}{2\pi j t}\right)^{\alpha-2} \left[P(\alpha-1, -2\pi^2 jt) - P(\alpha-1, 2\pi^2 jt)\right], \tag{10}$$

where $P(a, x) = \int_0^x t^{a-1} e^{-t}$ is the incomplete Gamma function. The incomplete integral can be approximated by using the power series expansion as:

$$P(a, x) = x^a e^{-x} \sum_{n=0}^{n=\infty} x^n / a(a+1)(a+2)\cdots(a+n). \tag{11}$$

For optimally using the correlation information to achieve the best quality of prediction, we need to study the time-dependence of the correlation function. Specifically, for our predictive bandwidth allocation purpose, the time granularity of interest is the frame duration, which is on the order of a few milliseconds. For this specific case, we can approximate the expansion in (11) to a limited number of terms as $t \to 0$. Accordingly, the the expression for $r(t)$ is reduced to:

$$r(t) = \left[\frac{(-\pi)^{\alpha-1} e^{-2\pi^2 jt}}{\alpha} - \frac{\pi^{\alpha-1} e^{2\pi^2 jt}}{\alpha}\right]. \tag{12}$$

In the following section, before describing the performance results of our proposed PDPS strategy, numerically computed results on the effect of traffic burstiness on the required order of linear prediction are exclusively discussed.

[1] Clearly, if the arrival process is Poisson (and hence memoryless), there is no need to look at the history for prediction, as the best prediction of new arrivals over a frame duration T will be the average λT, where λ is the traffic arrival rate.

5. Results and Discussion

Using MATLAB we conducted numerical computation and access network simulation studies. First, the impact of traffic burstiness on the optimum prediction order is studied without differentiating the traffic classes. Next, the performance of our proposed PDPS strategy is studied for P0, P1, and P2 service classes.

5.1. Evaluation of Quality of Prediction

To study the effect of prediction order, the prediction interval was chosen as 2 ms, which is our considered frame duration (as discussed in Section 5.2). In Fig. 4, the actual traffic (number of packets) per frame versus estimated traffic

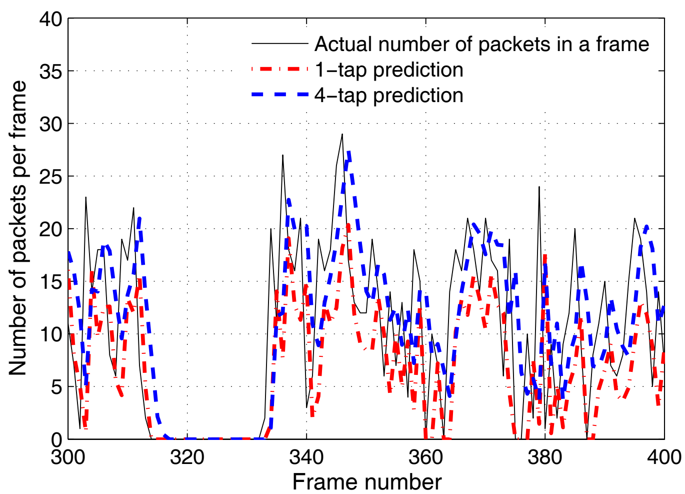

Figure 4: Comparison of predicted traffic with the actual arrivals. Burstiness parameter is $\alpha = 1.2$. The number of taps taken in the linear predictor are varied.

is shown, where the traffic burstiness parameter $\alpha = 1.2$, and different values of prediction order are considered. A close look at the effect of prediction order reveals that, with a lesser number of taps the sharp changes in traffic pattern is not tracked as closely as in the case with a higher number of predictor taps. This poor tractability of traffic pattern implies that a lesser prediction order would cause traffic under-prediction, leading to poorer QoS support and inefficient bandwidth usage. It may also be noted that, the LMS algorithm ensures that over-prediction does not happen with an increased prediction order. However, with a higher number of taps, there is a marginal increase in lag in predicted traffic, which can have a detrimental effect on the quality of prediction. Thus, an optimal number of taps has to be chosen to make best use of the channel resource.

Further, the time variation of autocorrelation coefficient was studied at different α. Fig. 5 shows the impact of burstiness of traffic on the correlation coefficient. The plots for $\alpha = 1.2$ (i.e., more bursty traffic) and $\alpha = 1.8$ (i.e., less bursty traffic) clearly indicate that, a traffic with higher burstiness would require more number of predictor taps, as

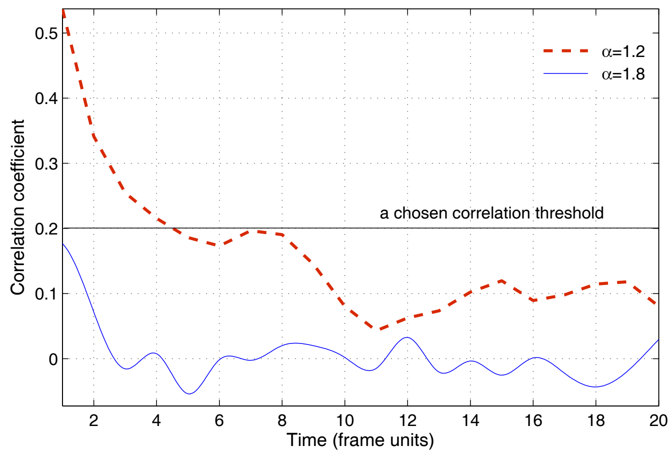

Figure 5: Variation of correlation coefficient r with time in frame units for different burstiness parameter α.

the packet count correlation (obtained using (12)) is higher and also it decays more slowly. If we choose the minimum correlation threshold as $r_{th} = 0.2$, number of taps required for a traffic having $\alpha = 1.2$ is nearly 4, whereas for $\alpha = 1.8$ only 1 tap is sufficient to achieve a similar quality of prediction. Therefore, a universal choice of 4 taps for any type of traffic, as suggested in [8], would mean unnecessary processing overhead without achieving any additional appreciable gain from prediction.

Now suppose we have 10 customers of a particular class of traffic. The system uses predictive scheduling, and the bandwidth allocated in a frame of 2 ms is directly proportional to the demand of the customers. The system bandwidth (line rate) is taken 1 Gbps and the traffic arrival is assumed to be Pareto distributed. The variation of average access delay of customers versus traffic load is plotted in Fig. 6 for different burstiness parameter α, where the *access delay is defined as the average time between enqueueing a packet in the buffer and sending out the last bit of the packet*. It can be seen from the figure that the gain in delay performance by using more taps in linear prediction is more for more bursty traffic, because it has a higher correlation and it decays over a longer time relative to the less bursty traffic (as indicated in Fig. 5). However, with the increase in number of taps, the gain achieved in terms of average delay decreases, as the correlation coefficient decreases with time. It is also evident from Fig. 6 that we need to use more number of taps for more bursty traffic to match the delay performance of less bursty traffic with a fewer number of taps. For example, a 6-tap prediction for $\alpha = 1.2$ is needed to obtain a similar performance as for $\alpha = 1.8$ with a 1-tap predictor.

5.2. Performance Results on Our PDPS Strategy

We tested our proposed strategy for P0 (packetized voice), P1 (video), and P2 (data) service classes. Unless otherwise mentioned, P0 traffic constituted 10% of the load and the remaining load was divided equally between P1 and P2. As per G.723.1 voice coder spec, P0 packet size was fixed at 70 Bytes. Since P1 traffic is highly bursty,

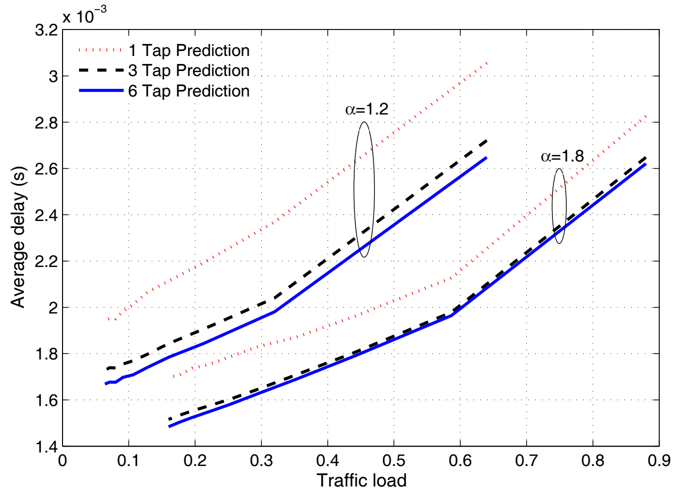

Figure 6: Access delay performance for different burstiness and different number of taps of the predictor.

the considered packet size of P1 streams ranges from 64 to 1518 Bytes. P2 packet size was also considered variable between 64 to 1518 Bytes. The packet arrival processes for all classes were considered Pareto distributed, with the value of burstiness parameter α taken as 2, 1.2, and 1.5, for P0, P1, and P2 traffic, respectively. The packet sizes for P1 and P2 classes were generated as truncated exponentially distributed. The SLAs of different classes were computed by accounting for the respective traffic arrival rates and average packet lengths.

In all cases, TDMA cycle time was 2 ms. For P0 class, ITU-T G.1010 suggested end-to-end delay is 150 ms and packet loss rate is 1%. Hence, for voice traffic access performance, allowable delay was studied to maintain nearly 1% loss rate. For P1 class, ITU-T G.1010 specified end-to-end delay is 2 s and loss rate is 3%. Accordingly, in this study no restriction was imposed on video packet access delay, i.e., the waiting video packets were allowed to enqueue beyond the current frame. Number of ONUs considered was 16, and the line rate was taken 1 Gbps. Maximum distance between an ONU and the OLT is 20 km, which is nearly the maximum distance permitted in a typical EPON. So, as per the IEEE 802.3ah standard's target, in order to avoid collision of packets from adjacent ONUs due to different propagation delay and synchronization inaccuracies, the guard time between adjacent slots was taken 1 μs.

We compared our proposed PDPS strategy with respect to the DBA [6] and SLA-DBA [5] strategies, which are closest to our proposed service class differentiated scheduling policy. The respective properties of these two approaches are outlined in Section 1. In DBA, only for the voice traffic the SLA is consulted, which was set at 9% for our chosen traffic ratios. For the SLA-DBA, the lower limits of SLAs for voice and video were set respectively at 9% and 14%, and the corresponding upper limits are 41% and 50%. For PDPS, the SLAs for voice and video were respectively 9% and 50%. Note that, for a different ratio of the three priority classes, the respective SLAs will be different.

Fig. 7 shows the average access delay performance of voice (P0) traffic. The X-axis represents the total load of an ONU, which is uniform across all ONUs. In this aspect of study, no restriction on maximum delay limit of voice

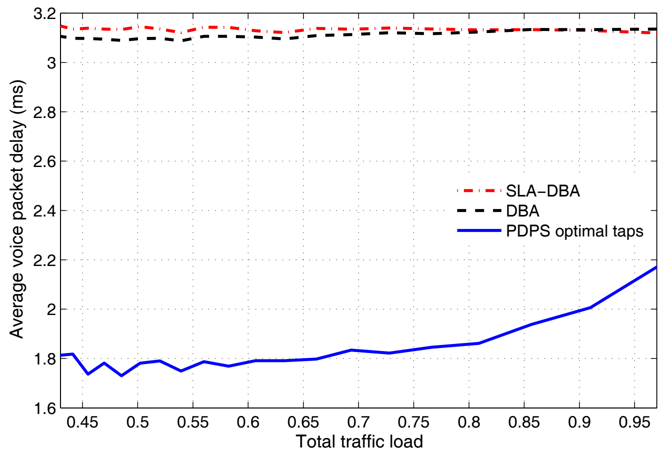

Figure 7: Average access delay performance of packetized voice (P0) traffic.

packets was imposed. Since the voice traffic is less bursty (with chosen $\alpha = 2$), single tap predictor is found to offer the minimum delay performance in PDPS. Also, since the maximum resource allocation to voice traffic in PDPS is strictly SLA based, its access performance is independent of the prediction quality of video and data traffic. Relative performances of DBA and SLA-DBA indicate that, a gain (reduction) of nearly 2 ms (i.e., one frame duration) delay is achieved by predictive resource requests even at a very low system load. Further gain in PDPS is achieved at higher loads due to class-based judicious traffic predictions and minimized unused bandwidth allocations. SLA-DBA performance is a little poorer than DBA because SLA-DBA does not ensure strict SLA guarantee of voice traffic; rather it is linked with the traffic burstiness of the other classes.

The loss rate performance of voice traffic is strictly a function of tolerable delay limit and the traffic distribution ratios. To have a reasonable loss rates in all allocation strategies, we have set the maximum delay bound of a packet at about 3.7 ms. Thus, for voice packet loss study, a voice packet at the ONU is discarded if it has already incurred a 3.7 ms delay in waiting. As shown in Fig. 8, with our considered traffic ratios, this imposed delay limit causes a loss rate up to 5% in PDPS. Since the average access delays in DBA and SLA-DBA are quite high (as shown in Fig. 7), the imposed 3.7 ms delay limit also results in a higher voice packet loss rate, which is above 25%. It may also be noted from Figs. 7 and 8 that, the delay and loss performance of the voice packets in DBA and SLA-DBA almost do not increase with load, which is because of higher SLAs (in DBA due to fixed resource assignment to P0 traffic, and in SLA-DBA due to a higher SLA-max), so as to avoid high packet loss rate. In PDPS, there is an appreciable increase in delay and loss rate performance at a high system load, which could be caused by the error introduced by the lag in traffic prediction while taking advantage of the flexible lower limit of SLA for P0 traffic. Although the error is magnified at a high system load, the overall system performance of PDPS (as would be seen through the subsequent

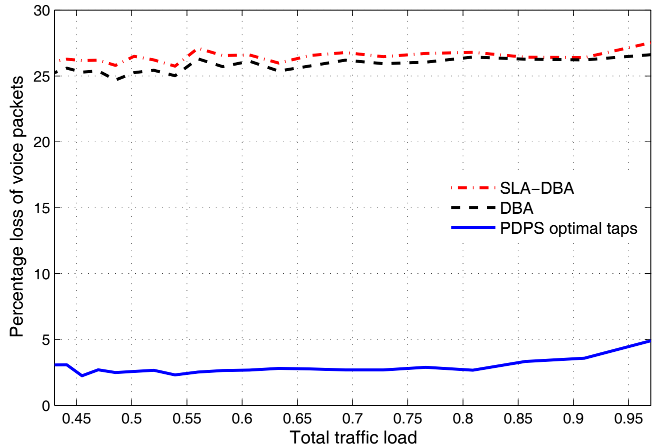

Figure 8: Packet loss rate performance of voice (P0) traffic.

results) is still higher.

Average access delay performance of video (P1) traffic is shown in Fig. 9. For video traffic with $\alpha = 1.2$, the optimum prediction order was found to be 4, as beyond this number of taps no significant reduction in video access delay was observed. The combined effect of predictive bandwidth request, minimized bandwidth waste, and strict

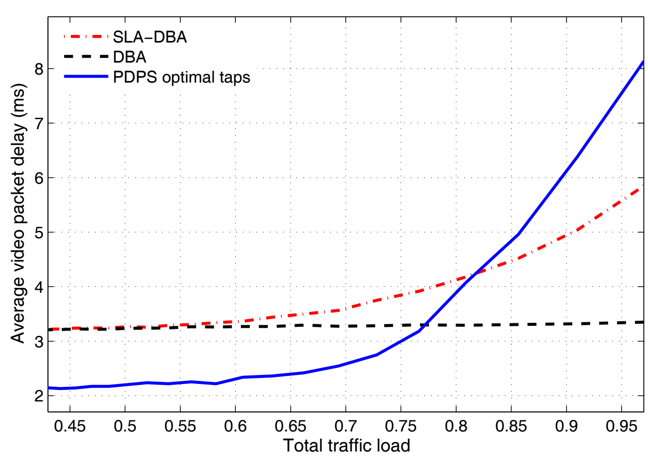

Figure 9: Access delay performance of video (P1) traffic.

priority scheduling in PDPS results in a reduced delay of P1 traffic up to a moderately high system traffic load. With the chosen $10\% : 45\% : 45\%$ traffic ratio, an increasingly poorer PDPS performance over that of the SLA-DBA could be a result of prediction error, which is magnified at higher traffic loads and at higher ratios of bursty traffic (P1 and P2 classes). We conjecture this prediction error is caused by the delay of the predictor in tracking the actual traffic pattern. Although the overall performance of PDPS is better than that of DBA and SLA-DBA, more investigations are required on designing newer prediction algorithms to further improve upon the traffic prediction.

Since DBA allocates the demand for bursty video traffic (and allocates voice SLA) before addressing the bandwidth requirements of data traffic, video traffic delay in DBA is seen increasingly better compared to PDPS and SLA-DBA as the system load is increased. The cost of this improved video access delay performance of DBA is visible in QoS performance of other traffic classes as well as in overall system throughput, as discussed through the subsequent results.

Fig. 10 shows the access delay of data (P2) traffic, where, for PDPS the optimum number of taps in the data traffic predictor was found to be 3. The results clearly show that, beyond a moderate system load the delay of data packets

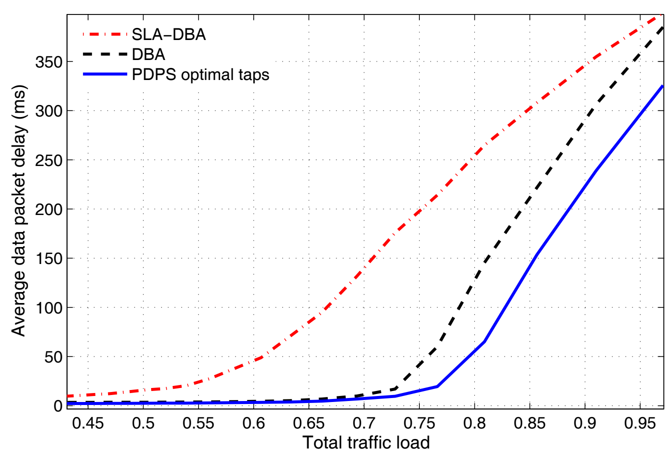

Figure 10: Access delay performance of data (P2) traffic.

in DBA as well as SLA-DBA sharply increases and is much higher than that offered by the PDPS, which is due to the bandwidth allocation policy of DBA and SLA-DBA, as discussed in video traffic performance results. Thus, the combined effect of strict priority awareness and predictive bandwidth request in PDPS is that, it handles the increased system load more gracefully compared to DBA and SLA-DBA. We noted that, the PDPS has a clear 2 ms reduced data packet delay performance even at a very low load. However, because of sharp rise in data packet delays in DBA and SLA-DBA at higher system loads, the distinct performance difference of PDPS at lower loads is not visible in the plots. It may also be noted that, the SLA-DBA performs poorer than DBA in the shown range of system load.

Fig. 11 shows the system throughput performance, wherein the delay constraint of voice packets are removed for a close comparison. The throughput with PDPS is found higher than that of DBA as well as SLA-DBA, which is more prominent at a moderate to high system load. SLA-DBA performance is found worst among the three, which is because, at a high ratio of data traffic, while trying to allocate some resource to the data traffic the delay performance of video traffic and hence the overall throughput in SLA-DBA deteriorates. We have noted that, this trend however

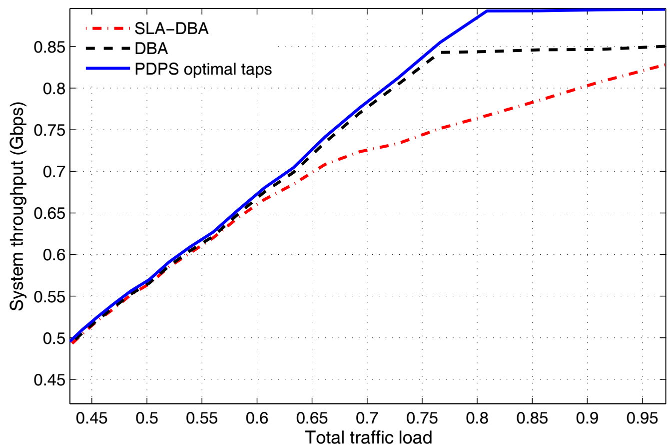

Figure 11: Network access throughput performance.

significantly reverses and the delay and throughput performances of DBA sharply reduces below that of SLA-DBA at a higher ratio of video traffic as well as at a higher system load. The throughput plots with voice delay constraint, which is omitted to avoid repetition, showed a more distinct gain in throughput with PDPS, as DBA and SLA-DBA have more voice packet losses due to the inherent higher delay, and the unused bandwidth remains unutilized.

In Table 1, the effect of adjusting the traffic characteristics dependent number of taps in the LMS filter is shown in terms of reduced access delay of video (P1) and data (P2) traffic and increase in overall system throughput. The

Table 1: System performance gain (reduced access delay (ms) and increased system throughput (kbps)) with traffic burstiness dependent optimal number of taps. Nominal number of taps is 1. Optimal number of taps for video (with $\alpha = 1.2$) is 4, and that for data (with $\alpha = 1.5$) is 3.

Traffic ratio	**Load 0.3**			**Load 0.52**			**Load 0.91**		
(voice:video:data)	**video**	**data**	**throughput**	**video**	**data**	**throughput**	**video**	**data**	**throughput**
70:20:10	0.008	0.3	45	0.02	0.3	188	0.48	0.36	250
33:33:33	0.01	0.36	76	0.04	0.36	176	0.1	0.84	400
20:70:10	0.01	0.3	72	0.1	0.4	164	2.4	4.1	1500

voice traffic (P0) being the least bursty (with $\alpha = 2$), beyond a nominal 1-tap predictor no significant gain in delay performance was achieved. Since the resource assignment to the P0 class is independent of the demands from P1 and P2 classes, the optimality of number of taps for P1 and P2 classes do not affect the access performance of P0, and hence it is not shown in the table. Also, as discussed in Figs. 9 and 10, for video and data traffic, the optimum number of taps were found 4 and 3, respectively. With these optimum predictors, the performance improvement is more when the ratio of video (P1) traffic is more, as there is more room to gain from the bursty environment by a closer prediction.

At a high system load, the gain in system throughput is about 2.5 Mbps, and the percentage gains (reductions) in access delay performance of video and voice are found substantial. Specifically, the maximum reduction in delay of video traffic is on the order of 14% – which is achieved when the traffic ratios are equal for all classes and at a high system load, whereas the gain for the data traffic is consistently between 17% and 20% – irrespective of the traffic ratio and system traffic load. Overall, the results clearly indicate that: (i) a rudimentary choice of a basic 1-tap predictor does not fully exploit the benefits of traffic prediction; (ii) it is important to adapt the prediction order with the level of traffic burstiness, which can achieve the best possible system performance without unnecessarily incurring a high prediction-related processing overhead.

6. Conclusion

We have proposed a strict QoS aware predictive dynamic priority scheduling for the uplink bandwidth access in EPONs. We showed that the traffic burstiness has a clear effect on the optimum prediction order, and identified the required minimum number of taps that tangibly aids prediction. This burstiness-dependent reduction in prediction order is expected to help reduce the processing overhead of the predictor. Further, via simulations we demonstrated that, by judiciously distributing the bandwidth among the priority classes and applying a standard linear traffic prediction strategy with burstiness-dependent optimal number of taps, a lesser loss rate as well as delay of priority classes and a higher access network throughput can be achieved.

Although the optimum linear predictor was found to offer an overall improved system performance, to address the prediction error caused by delayed tracking of the actual traffic, more advanced prediction algorithms are to be investigated.

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[1] G. Kramer, B. Mukherjee, S. Dixit, Y. Ye, R. Hirth, On supporting differentiated classes of service in EPON-based access network, J. Opt. Networks 1 (8-9) (2002) 280–298.

[2] M. Ma, Y. Zhu, T. H. Cheng, A bandwidth polling MAC protocol for Ethernet passive optical networks, in: Proc. IEEE INFOCOM, San Francisco, CA, USA, 2003, pp. 22–31.

[3] C. M. Assi, Y. Ye, S. Dixit, M. A. Ali, Dynamic bandwidth allocation for quality-of-service over Ethernet PONs, IEEE J. Sel. Areas in Commun. 21 (9) (2003) 1467–1477.

[4] Y. Luo, N. Ansari, Bandwidth allocation for multiservice access on EPONs, IEEE Optical Commun. Mag. 43 (2) (2005) s16–s21.

[5] D. Nowak, J. Murphy, P. Perry, Bandwidth allocation in DiffServ-enabled Ethernet passive optical networks, IET Commun. 3 (3) (2009) 391–401.

[6] S.-I. Choi, J.-D. Huh, Dynamic bandwidth allocation algorithm for multimedia services over Ethernet PONs, ETRI Journal 24 (6) (2002) 465–468.

[7] H.-J. Byun, J.-M. Nho, J.-T. Lim, Dynamic bandwidth allocation algorithm in Ethernet passive optical networks, IEE Electronic Letters 39 (13) (2003) 1001–1002.

[8] Y. Luo, N. Ansari, Limited sharing with traffic prediction for dynamic bandwidth allocation and QoS provisioning over EPONs, OSA J. Optical Networking 4 (9) (2005) 561–572.

[9] D. Morato, J. Aracil, L. A. Diez, M. Izal, E. Magana, On linear prediction of Internet traffic for packet and burst switching networks, in: Proc. IEEE ICCCN, Scottsdale, AZ, USA, 2001.

[10] S. A. M. Ostring, H. Sirisena, The influence of long-range dependence on traffic prediction, in: Proc. IEEE ICC, Helsinki, Finland, 2001.

[11] G. Kramer, B. Mukherjee, G. Pesavento, Ethernet PON: design and analysis of an optical access network, Photonic Network Commun. 3 (3) (2001) 307–319.

[12] G. Kramer, B. Mukherjee, G. Pesavento, IPACT: a dynamic protocol for Ethernet PON (EPON), IEEE Commun. Mag. 40 (2) (2002) 74–80.

[13] J. Zheng, Efficient bandwidth allocation algorithm for Ethernet passive optical networks, IEEE Proc. Commun. 153 (3) (2006) 464–468.

[14] S. Shenker, C. Partridge, R. Guerin, Specification of guaranteed quality of service, IETF Internet draft, `http://www.ietf.org/rfc/rfc2212.txt`.

[15] I.-S. Hwang, Z.-D. Shyu, L.-Y. Ke, C.-C. Chang, A novel early DBA mechanism with prediction-based fair excessive bandwidth allocation scheme in EPON, Elsevier Computer Commun. 31 (2008) 1814–1823.

[16] S. Haykin, Adaptive Filter Theory, Prentice Hall, 4th Ed., 2001.

[17] J. Gordon, Pareto process as a model of self-similar packet traffic, in: Proc. IEEE GLOBECOM, Singapore, 1995, pp. 2232–2236.