A Dynamic Offset and Delay Differential Assembly Method for OBS Network

Zhicheng Sui, Shilin Xiao, and Qingji Zeng

Abstract: **We study the dynamic burst assembly based on traffic prediction and offset and delay differentiation in optical burst switching network. To improve existing burst assembly mechanism and build an adaptive flexible optical burst switching network, an approach called quality of service (QoS) based adaptive dynamic assembly (QADA) is proposed in this paper. QADA method takes into account current arrival traffic in prediction time adequately and performs adaptive dynamic assembly in limited burst assembly time (BAT) range. By the simulation of burst length error, the QADA method is proved better than the existing method and can achieve the small enough predictive error for real scenarios. Then the different dynamic ranges of BAT for four traffic classes are introduced to make delay differentiation. According to the limitation of BAT range, the burst assembly is classified into one-dimension limit and two-dimension limit. We draw a comparison between one-dimension and two-dimension limit with different prediction time under QoS based offset time and find that the one-dimensional approach offers better network performance, while the two-dimensional approach provides strict inter-class differentiation. Furthermore, the final simulation results in our network condition show that QADA can execute adaptive flexible burst assembly with dynamic BAT and achieve a latency reduction, delay fairness, and offset time QoS guarantee for different traffic classes.**

Index Terms: **Burst assembly time (BAT), dense wavelength division multiplexing (DWDM), Internet protocol (IP), optical burst switching (OBS), quality of service (QoS).**

I. INTRODUCTION

Optical burst switching (OBS) [1] which combines the advantages of both circuit switching and packet switching and avoids their shortcomings becomes one of the most promising switching paradigms in design and implementation for optical backbone Internet protocol/dense wavelength division multiplexing (IP/DWDM) networks. OBS supports bufferless one-way fast resource reservation and asynchronous transmission of variable sized packets. OBS network is composed of edge nodes and optical switching core nodes. In the network, the edge nodes connect legacy interfaces such as Ethernet, asynchronous transfer mode (ATM), (synchronous optical network/synchronous digital hierarchy) SONET/SDH, and IP routers to core nodes. A source node sends a control packet which contains burst length and routing information, and then starts burst transmission after an offset time without receiving any acknowledgement from destination node. At core nodes, control packet is electronically processed, while offset time allows finishing control process and photonic switch configuration ahead of burst arrival. Thus core nodes estimate burst start and end time and then reserve a wavelength efficiently for transmitting burst. The data burst is switched through transparently with no examination or interpretation of optical data.

Burstification is an important issue in OBS, including length-based and timer-based assembly. Aggregation and classification of access packets with different encapsulation formats are critical to the performance of OBS network. Burst assembly and offset time introduce extra electronic buffer delay called assembly delay in traditional methods [2], [3]. Total assembly delay of an optical burst is the sum of buffering time for all electronic packets from arrival to departure. Moreover, just enough time (JET) protocol uses extra offset time to support prioritized service differentiation. Therefore an optical burst must wait assembly time and offset time to transmit that is too large compared with end-to-end propagating delay, which decreases the utilization of OBS network drastically and loses the guarantee for high priority service.

To enhance the flexibility of burst assembly, several adaptive assembly methods are put forward. An adaptive burst assembler [4] based on buffer overflow probability is given which needs to calculate the mean and variance of real-time traffic. Another adaptive assembly algorithm for TCP/IP packets [5] is proposed. In [6], hysteresis is used to realize adaptive assembly. However, all above adaptive assembly methods still have large delay and ignore latency reduction, delay fairness, and offset time quality of service (QoS) support for differentiated service. On the other hand, burst length-based assembly with segmentation QoS policy [7] is proposed, but it does not involve in assembly QoS guarantee. QoS burstification with relative delay fairness is proposed in [8] by disordering arrival packets. Unfortunately, the two methods do not consider absolute delay reduction and offset time QoS.

The study about delay reduction of burst assembly at edge node is based on traffic linear prediction [9], [10], however the predictive precision of the existing methods fluctuates with offset time and assembly time. So, the predictive methods may generate large estimate error and deteriorate the performance of OBS network extremely. Furthermore, the burst assembly granularity is preserved beforehand and inflexible to actual network traffic, which increases overhead and delay. The restrained factors increase network burden and deteriorate its performance. The traditional burst assembly mechanism aggravates network delay and degrades its robustness. Consequently, it is significant to present an effective dynamic burstification scheme to process real-time traffic, reduce assembly delay and provide QoS guarantee for different priority traffic at edge nodes. In this paper, we propose a QoS based adaptive dynamic assembly (QADA)

Manuscript received November 24, 2004; approved for publication by Krishna Sivalingam, Division III Editor, October 6, 2005.

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method for self-similar traffic to improve existing burst assembly mechanism. QADA method with one-dimension and two-dimension limit is compared under different prediction time and QoS based offset time. Simulation results show that QADA with current arrival traffic weight can obtain little delay by dynamically adjusting burst assembly time (BAT) and provide adaptivity, flexibility, delay fairness, and offset time QoS for different traffic burst assembly.

The rest of this paper is organized as follows. Section II describes the burst assembly system model based on prediction and offset time at OBS edge node, and in Section III, we propose the QADA method. In Section IV, we explain the performance evaluation of the proposed method and numerical results are shown. Finally, conclusions are presented in Section V.

II. SYSTEM MODEL

BAT lies on many factors such as the number of accessing sources, offered load, service classes, bit rate and network capacity. In view of current optical switching and control packet processing speed, offset time ranges from several hundred microseconds to millisecond order of magnitude, almost the same as assembly time. Our burst assembly and offset time system model at edge node utilizes JET protocol [11] as shown in Fig. 1. T_p is prediction time and T_o^i is offset time. C_0, C_1, C_2, and C_3 present four traffic classes from high to low priority. T_a^i denotes the BAT of C_i. We normalize prediction and offset time to assembly time. The offset time T_o^i is 0.3, 0.2, 0.15, and 0.1 for $C_0 \sim C_3$ to realize QoS in core OBS network. The different maximum BAT for four classes is set to guarantee delay differentiation. The one-dimension and two-dimension used here denote different BAT limited ranges. One-dimension has the same smallest BAT value, so the dynamic ranges of four classes overlap. However, the BAT ranges of two-dimension for four classes are rigidly separated. Fig. 1 gives two cases of prediction time: (a) $T_p = 0.2$. The limited one-dimensional dynamic BAT ranges for $C_0 \sim C_3$ are [0.5, 0.6], [0.5, 0.8], [0.5, 0.9], and [0.5, 1]. Two-dimensional BAT ranges are [0.5, 0.6], [0.6, 0.8], [0.8, 0.9], and [0.9, 1], respectively; (b) $T_p = 0.1$. The one-dimensional dynamic BAT ranges for $C_0 \sim C_3$ are [0.4, 0.5], [0.4, 0.7], [0.4, 0.9], and [0.4, 1]. Two-dimensional BAT ranges are [0.4, 0.5], [0.5, 0.7], [0.7, 0.9], and [0.9, 1], respectively. The different BAT ranges of one-dimension and two-dimension limit are used to realize differential burst assembly in OBS network. The high priority service can tolerate smaller burst assembly delay while the low priority service can bear larger delay. Every class executes dynamic burst assembly in its own BAT range.

In our QADA method, offset time T_o^i of the four classes are different and every burst can reduce the delay of an offset time T_o^i. Burst assembly time includes T_p and T_o^i. Each burst length is estimated in prediction time according to the past p-order burst length and current arrival traffic in T_p. At the end of prediction time, edge node estimates the burst length and then determines the dynamic BAT by current actual arrival size and estimate burst size. The general relation of T_p, T_o^i, and T_a^i in a certain assembly queue is shown in Fig. 1(c). Control packet is sent to OBS core network at $T = T_a^i - T_o^i$. Once burst assembly is over, we compare the estimate value with the actual burst

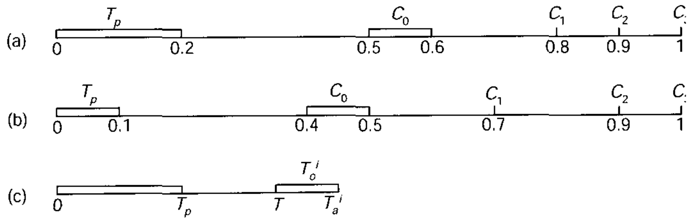

Fig. 1. Edge node assembly and offset time system model.

length value and obtain the length estimate error to fill with void or insert to the next data burst.

III. QADA METHOD

The MMSEP is a minimum mean square error linear predict method which is used for on-line dynamic bandwidth allocation to support variable bit rate (VBR) video traffic [12]. The k-step value $x(n+k)$ is predicted by a linear combination of the current and previous values of $x(n)$. Based on the normalized MMSEP algorithm for self-similar traffic, QADA method interpolates a current traffic weight in prediction time to improve the estimation performance of real-time traffic by adaptive auto-regressive (AAR) linear filter. This enhances prediction precision and reduces burst assembly delay greatly. Furthermore, QADA utilizes dynamic burst assembly based on delay fairness and QoS differentiation which is flexible and adaptive to real-time traffic in IP and Ethernet centric data network now. We consider the following four steps to outline the QADA method:

Step1: Set initial BAT value T_m^i for traffic class i. The first packet arrival at the corresponding port and service class assembly queue triggers the related AAR linear filter. Simultaneously, the previous prediction value $L(n)$ and the previous actual value $l(n)$ of burst length are used to calculate the error $e(n) = l(n) - L(n)$ and weight $\omega(i)$ $i = 0, \cdots, p-1$ in (2). Packets in the queue accumulate continually during T_p.

Step2: At the end of T_p, burst assembly queue passes the current arrival traffic $l(n+1)$ to AAR filter. Then QADA calls the past p-order burst length value $l(n-i), i = 0, \cdots, p-1$, and combines $\omega(i)$ with current arrival traffic info $l(n+1)$ to estimate the burst length $L(n+1)$. Expressions (1) and (2) give the description of the one-step burst length estimation $L(n+1)$. The coefficient $\omega(-1)$ is the weight of current arrival traffic $l(n+1)$ in prediction time T_p, which is the ratio weight of initial BAT T_m^i to T_p. The coefficients $\omega(i)$ $i = 0, \cdots, p-1$, are initialized to W_0, and α to $1 - W_0$ in (1). If $0 < \mu < 2$ in (2), Expression (1) will converge at the mean. Furthermore, the larger μ results in faster convergence, so we set $\mu = 1$ here.

$$L(n+1) = \sum_{i=0}^{p-1} \omega(i) l(n-i) + \alpha l(n+1) \frac{T_m^i}{T_p} = \sum_{i=-1}^{p-1} \omega(i) l(n-i) \tag{1}$$

$$\vec{\omega}(n+1) = \vec{\omega}(n) + \frac{\mu[l(n) - L(n)]\vec{l}(n-1)}{\|\vec{l}(n-1)\|^2} \tag{2}$$

$$\vec{\omega} = [\omega(0), \omega(1), \cdots, \omega(p-1)]^T$$

$$\vec{l}(n) = [l(n), l(n-1), \cdots, l(n-p+1)]^T.$$

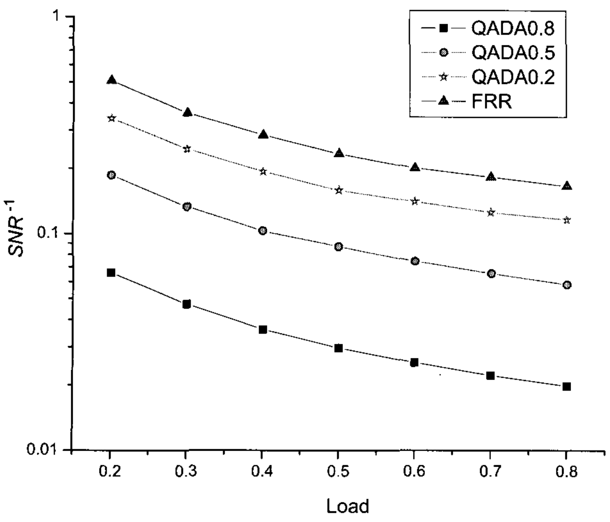

Fig. 2. SNR^{-1} vs. load.

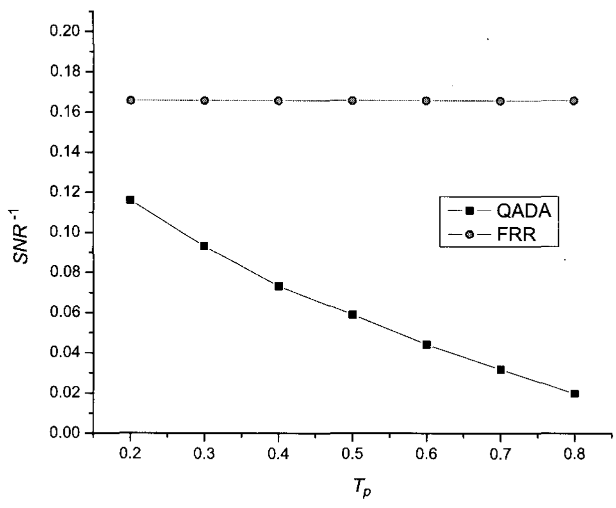

Fig. 3. SNR^{-1} vs. T_p.

Step3: QADA calculates BAT (3) with offered load and assures T_a^i within the corresponding limited BAT dynamic range. The dynamic range is classified into one-dimension and two-dimension limit as described in Fig. 1. If T_a^i is beyond the corresponding BAT range, its boundary is set to T_a^i. One-dimension limit augments the BAT dynamic range of all four classes, whereas two-dimension limit guarantees much stricter delay differentiation among the four classes. Then QADA adds estimate burst length $L(n+1)$ and T_o^i to optical control packet and sends control packet at the time $T = T_a^i - T_o^i$.

$$T_a^i = L(n+1) \times \frac{T_p}{l(n+1)}. \tag{3}$$

Step4: As soon as the data burst assembly completes at the end of T_a^i, QADA judges whether burst length estimate value $L(n+1)$ is more or less than the actual burst size $l(n+1)$ in current assembly queue. If $L(n+1) > l(n+1)$, then execute void filling; else if $L(n+1) < l(n+1)$, then keep the residual packets of $e(n+1) = l(n+1) - L(n+1)$ in the queue as the initial current arrival traffic $l(n+1)$ for the next prediction and wait to send with the next assembly burst together. Then QADA executes optical burst routing and wavelength assignment and multiplexes the burst with estimate size of $L(n+1)$ into optical fiber for transmission.

IV. PERFORMANCE EVALUATION

To evaluate the performance of the dynamic burst assembly technique under a various offered load, we undertake simulations in a network environment, along with the following assumptions:

- Forty 100 Mbps Ethernet sources access the edge node. Hurst parameter of packet inter-arrival process is 0.9.
- Every self-similar source generates packets of which the length follows Pareto distribution with the range from 64 bytes to 1518 bytes. The shape parameter of Pareto distribution is 1.4.
- The number of egress edge nodes is 15.
- The order of the AAR linear filter is four.

Firstly, SNR^{-1} of burst length prediction under different offered load and prediction time are given in Section IV-A. Then we analyze the burst assembly of one-dimension and two-dimension limit with different prediction time in Sections IV-B and IV-C. There are four performance parameters in our QADA method with offset time and delay differentiation: Burst length error, burst size, burst utilization, and delay.

A. Burst Length Prediction

The accuracy of the FRR method in [10] and the QADA method is assessed by the parameter: $SNR^{-1} = \sum e(n)^2 / \sum l(n)^2$ which is the inverse of signal-to-noise ratio (SNR). As shown in Fig. 2, we first study the relation of SNR^{-1} to offered load with $T_p = 0.2, 0.5, 0.8$. Whenever prediction time is small (0.2) or large (0.8), the performance of FRR is worse than QADA. SNR^{-1} versus different T_p at $load = 0.8$ is described in Fig. 3. The SNR^{-1} of FRR is 0.165673 larger than QADA all along. The above plots demonstrate that QADA is better than FRR method under different prediction time and offered load and QADA is suitable for the prediction of real scenarios. In terms of the burst length error SNR^{-1}, we can evaluate the range of acceptable values for the prediction time to predict real traffic arrivals. As long as the offered load is not too small (> 0.3), the burst length error with a larger prediction time (> 0.3) can achieve such a low level as under 5%$\sim$10%. Thus it can be seen that QADA method is perfect prediction for self-similar traffic.

Although QADA method obtains the good performance of prediction in a reasonable condition, there are still many tradeoffs among prediction time, offset time and the dynamic range of assembly time which interact on burst length error and delay reduction of each other. The smaller length error with a larger prediction time is at the cost of smaller offset time. Here, we only give a demonstration of the QADA method under a certain offset time and prediction time. We use small prediction time (0.2 and 0.1) with relative large dynamic range to observe the conspicuous dynamic assembly and differential delay for four

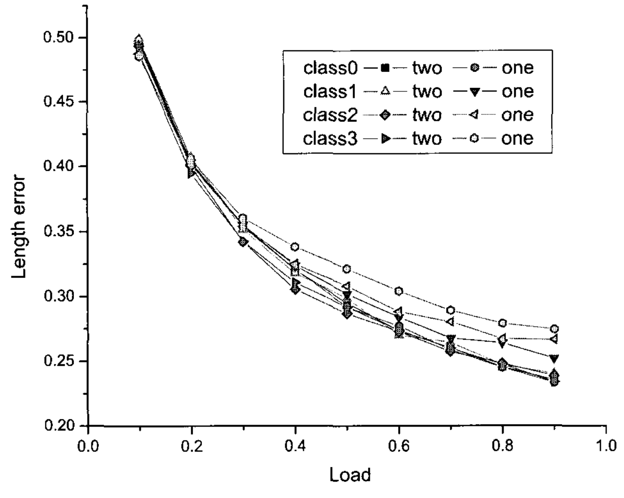

Fig. 4. Burst length error vs. load with $T_p = 0.2$.

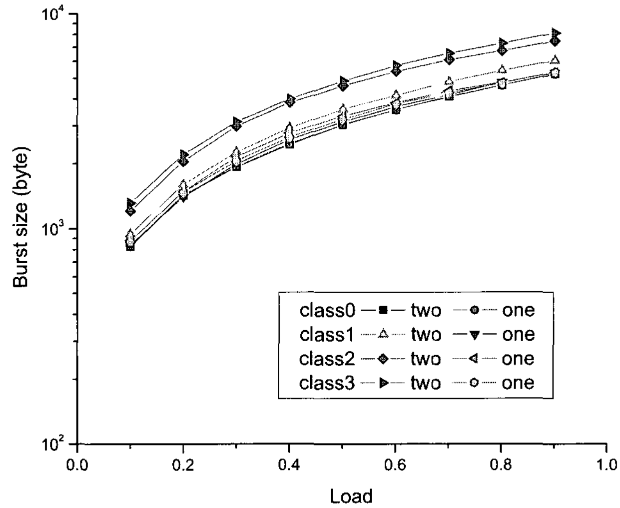

Fig. 5. Burst size vs. load with $T_p = 0.2$.

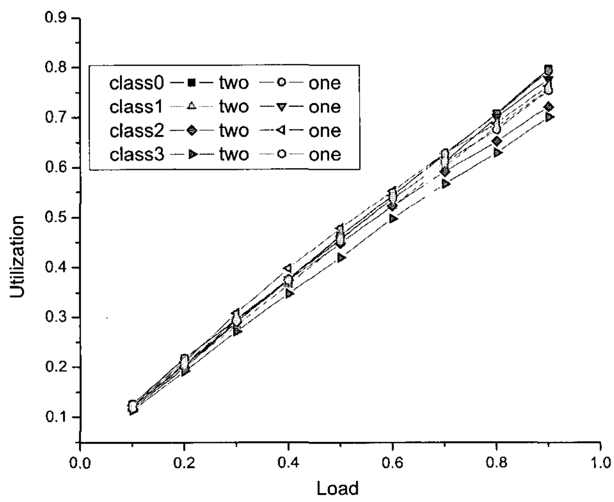

Fig. 6. Burst utilization vs. load with $T_p = 0.2$.

classes.

B. Comparison between One Dimension and Two Dimension

Figs. 4–7 show the performance comparisons for four traffic classes of QADA method in terms of one-dimensional and two-dimensional BAT range with $T_p = 0.2$ (Fig. 1(a)). As shown in Fig. 4, we investigate the variation of average burst length error which is the ratio of estimate error length to average burst length. All length errors decrease with the increase of offered load. The four traffic classes under two-dimensional assembly obtain approximately close prediction performance. The length error of two-dimensional BAT is nearly smaller than all classes of one-dimensional BAT. This demonstrates that our QADA method that chooses the optimal W_0 has almost no effect on two-dimension inter-class prediction. However, we also can see from Fig. 4 that one-dimensional length prediction errors differ for four traffic classes. The one-dimensional length error of high priority traffic is smaller than that of low priority traffic due to the relative long BAT of low priority traffic. Fig. 5 plots the average burst size of four classes and the burst size increases with the augment of offered load. Under one-dimensional BAT, the burst sizes of the four classes only achieve slight difference, whereas the burst size of high priority class is smaller than low priority class in two-dimensional assembly. The burst sizes of the four classes are dominated by strict BAT isolation but not the burst length predictive error. Consequently, the longer the average BAT is, the larger the burst size of the corresponding class is. This verifies that our two-dimensional QADA method realizes the BAT differentiation.

The dependence of average burst utilization versus offered load for four classes is described (Fig. 6). The burst utilization is defined as the sum of the total estimate packet time over BAT. The burst utilization increases steadily as the load turns large. The utilizations of the four classes in two-dimensional BAT are a little smaller than in one-dimensional BAT. Two-dimensional assembly obtains burst utilization differentiation. The higher the traffic priority is, the larger the burst utilization becomes. But within the one-dimensional assembly the average burst utilization of different classes is almost equal which indicates that our one-dimensional QADA method does not change the inter-class utilization. The slight distinguish of burst size and utilization among the four classes results from the overlap of one-dimensional BAT range which contributes little to delay differentiation.

In Fig. 7, the average burst assembly delay versus offered load are compared under one-dimensional assembly with two-dimensional assembly for traffic $C_0 \sim C_3$. We observe that burst assembly delay is small and becomes large along with the offered load increased. This incremental assembly delay ascribes to the more packets encapsulated by every burst. Burst average delay of high priority class is always smaller than that of low priority class. Under the preconditioning of QoS based offset time (i.e., T_o^i is 0.3, 0.2, 0.15, and 0.1 for $C_0 \sim C_3$) as mentioned in Section II, the plot indicates that QADA realizes delay differentiation successfully and achieve adaptivity and flexibility. Through comparison, it is easy to find out that the delay of one-dimensional assembly is smaller than that of two-dimensional assembly. Furthermore, since two-dimensional dynamic burst

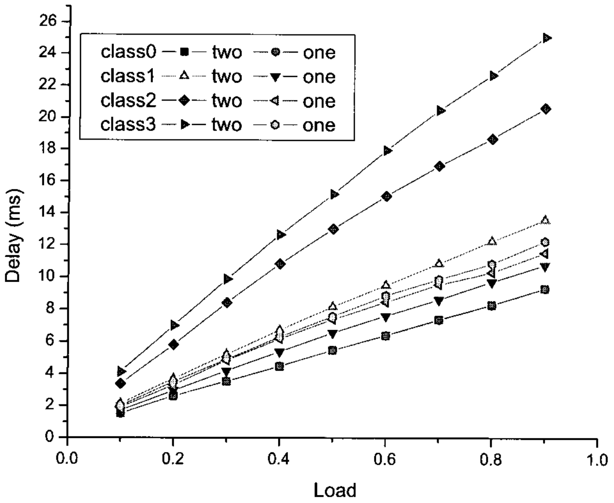

Fig. 7. Delay vs. load with $T_p = 0.2$.

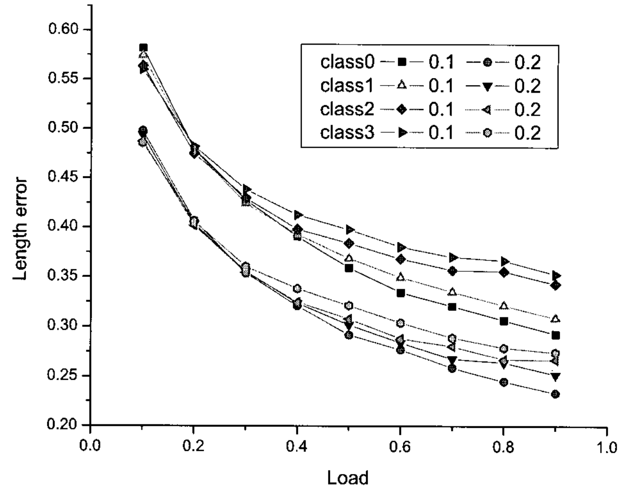

Fig. 8. Burst length error vs. load with one dimension.

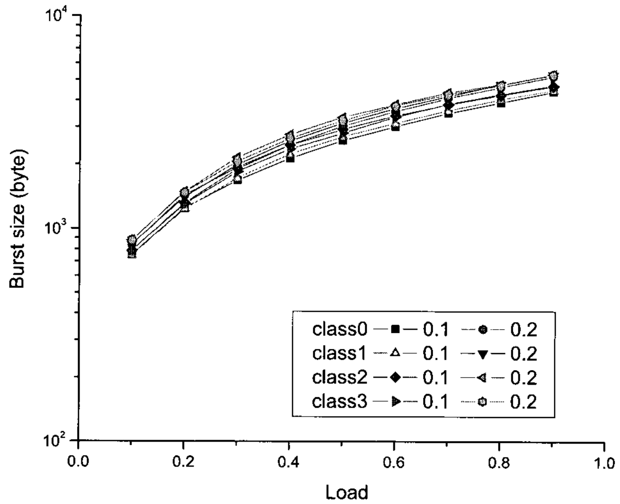

Fig. 9. Burst size vs. load with one dimension.

assembly owns absolutely different range with larger threshold, it achieves stricter differentiation though its average assembly delay of high priority class is much larger than one-dimensional assembly. Likewise, from the above analysis of Figs. 5 and 6 about one-dimensional assembly, we also deduce that the small one-dimensional inter-class delay is mainly caused by the overlapping dynamic BAT range. In addition, long prediction time brings small length error and then decreases the burst assembly delay when the sum of prediction time and offset time is constant.

C. Comparison between Prediction Time

The simulation and analysis in Section IV-B indicate that one-dimension brings less delay than two-dimension and also realizes the class differentiation. The small burst assembly delay of one-dimension is basically caused by the overlapping dynamic BAT ranges. However, the stricter class differentiation of two-dimension is at the cost of the larger burst assembly delay for high priority classes. On the other hand, we have evaluated the performance of one-dimension and two-dimension at $T_p = 0.2$. Therefore, in this part, we compare the performance of QADA at $T_p = 0.2$ (Fig. 1(a)) with $T_p = 0.1$ (Fig. 1(b)) for four traffic classes using one-dimensional assembly.

First, the average length error of QADA with variant offered load is depicted in Fig. 8. It decreases monotonously as the load turns large for each traffic class. Length error of $T_p = 0.2$ is smaller than $T_p = 0.1$ for all classes owing to the longer prediction time of current arrival traffic. They both realize differentiation between high and low priority traffic classes and the length error of high priority traffic is smaller than low priority class. Second, Fig. 9 shows the average burst size according to offered load. The burst sizes increase as the offered load increased. The burst size of $T_p = 0.1$ is a little smaller than that of $T_p = 0.2$ for reasons of the relative small one-dimensional dynamic BAT. Under different classes and prediction time, the burst sizes only achieve slight difference.

We examine the average utilization of $T_p = 0.2$ and $T_p = 0.1$ according to offered load from Fig. 10. The burst utilizations increase steadily as the load turns large. The utilizations of the four classes at $T_p = 0.1$ are a little larger than $T_p = 0.2$. But within the same T_p, the utilizations of different classes are almost equal which indicates that our QADA method does not change the inter-class utilization in this case. The slight distinguish of burst size and utilizations among the four classes results from the overlap of BAT range which contributes little to delay differentiation. Fig. 11 shows the impacts of offered load on average assembly delay for $C_0 \sim C_3$ which all increase with load. It can be seen that QADA method achieves the assembly delay differentiation. We also discover that, the average delay at $T_p = 0.2$ is always larger than that of corresponding service class at $T_p = 0.1$, because the former offers relative large dynamic BAT as depicted in Fig. 1. Burst average assembly delay of high priority class is always smaller than that of low priority class at a certain prediction time. Based on the analysis of Figs. 8–10, it can be explained that the inter-class prediction error plays an important role in the distinct delay differentiation among the four classes in one-dimensional assembly.

All the simulation results above imply the following conclu-

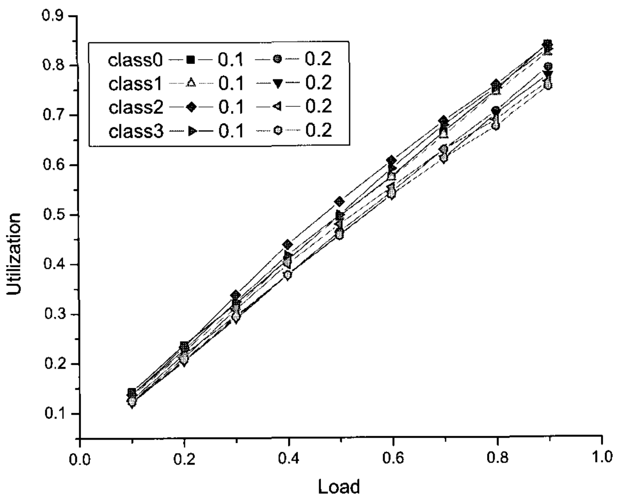

Fig. 10. Burst utilization vs. load with one dimension.

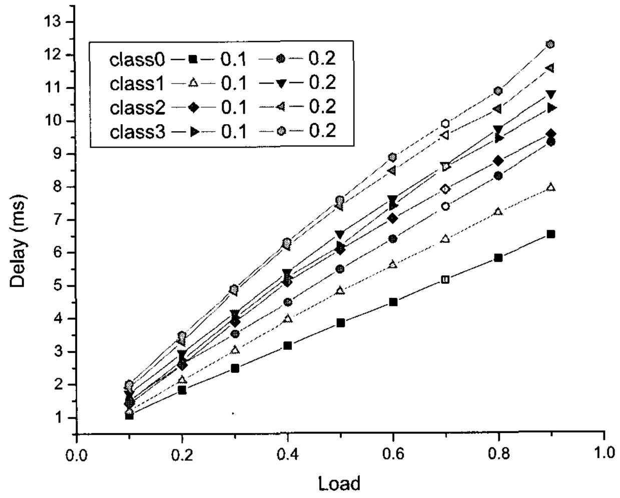

Fig. 11. Delay vs. load with one dimension.

sions. Firstly, QADA method can execute perfect prediction for the self-similar traffic in certain condition. In spite of introducing the assembly mechanism of the last residual packets being inserted to the next burst, the burst length error of QADA is tolerable even in the worst case of $T_p = 0.1$ and low load. The high error in our figure results from the very small ratio (prediction time is 0.2 or even 0.1) which means the burst length is estimated at one fifth or one tenth of an assembly time. Since the real Internet traffic can be best modelled by self-similar processes, the results strongly testify the adaptive feature of our QADA method. In fact, the length error lies on the ratio of the prediction time to assembly time and the prediction time can change according to different requirements. The prediction time, offset time and the dynamic BAT range can be adjusted by the actual environment of traffic load in real networks. As the prediction time of the four classes are designated the same value here and the BAT are different for the four classes, the relative prediction time ratio is large for high priority service and small for low priority service. For the sake of the lower length error tolerance, different prediction time ratio can also be exploited for the four classes.

Secondly, QADA adaptively adjusts the estimate burst length and then dynamically changes BAT for the minimum delay in a certain prediction time and QoS based offset time. QADA obtains adaptive optimal performance of dynamic BAT and assembly delay. The reduction of assemble delay and the improvement of burst utilization at edge node release the rigorous demand of end-to-end delay for real-time traffic, and furthermore enhance the throughput and efficiency in core OBS networks. Finally, the performance of QADA with one-dimensional assembly is better than two-dimensional assembly at $T_p = 0.2$, however, the latter can achieve better dynamic BAT differentiation and delay fairness among the four traffic classes. Moreover, by means of making prediction time of the four traffic classes close to their own dynamic BAT, QADA can offer better prediction precision and then improve the performance in two-dimensional assembly. Although the prediction length error at $T_p = 0.1$ is larger than $T_p = 0.2$ totally, QADA method at $T_p = 0.1$ outperforms $T_p = 0.2$ in terms of assembly delay and burst utilization in one-dimensional assembly. Simultaneously QoS based offset time provides QoS guarantee for four traffic classes in OBS core networks on the premise of no more extra assembly delay.

V. CONCLUSION

A QADA approach on traffic prediction for self-similar traffic is proposed to improve the burst assembly mechanism at the edge of OBS networks in this paper. We study the predictive SNR^{-1}, length error, burst size, burst utilization, and assembly delay for four traffic classes at different prediction time and offset time, and we introduce current arrival traffic in prediction time and adaptive linear prediction for self-similar traffic to perform adaptive dynamic assembly in limited BAT range. QADA method can estimate real-time network traffic character on-line, dynamically adjust BAT and then reduce assembly delay at edge node under various load. We compare two assembly methods between one dimension and two-dimension with different prediction time under QoS based offset time and find that, one-dimensional method appears rather better performance and two-dimensional method with longer prediction time can realize stricter inter-class differentiation. Simulation results in our network condition demonstrate that QADA can adaptively accommodate the change of traffic load, prediction time and offset time with limited dynamic BAT range, without increasing the complexity of existing algorithm and bandwidth signaling overhead. Furthermore, the flexible QADA approach provides delay fairness and offset time QoS guarantee for different priority traffic and achieves minimum assembly delay at edge node.

ACKNOWLEDGMENTS

This work is jointly supported by the National Natural Science Foundation of China (No.60572029) and the Optical Science and Technology Plan of Shanghai (No.036105004).

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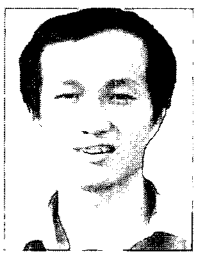

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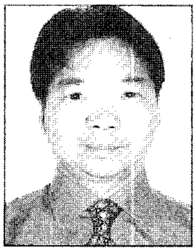

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