Proceedings of the 2002 IEEE
International Symposium on Intelligent Control
Vancouver, Canada • October 27-30, 2002

# Adaptive Admission Control of Multimedia Traffic in High-Speed Networks[1]

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***Abstract***—This paper proposes a novel real-time adaptive admission control (AAC) scheme with a desired quality of service (QoS) guarantee and high network utilization in high-speed networks. The QoS is given in terms of service delay, which is defined as the time it takes for a source to get admitted into the network after it initiates its intended request, packet/cell losses, and transmission delay (time taken to complete transmission from its initiation). AAC uses the following information- the available capacity from a novel adaptive bandwidth estimation scheme, a congestion indicator derived from a congestion controller, Peak Cell Rate (PCR) estimate from new sources, along with the desired QoS metrics, and outputs an 'admit' or 'reject' decision signal to the new sources while guaranteeing QoS and network utilization. Simulation results are presented by streaming ON/OFF and video data into the network. Results show that the p roposed AAC admits significantly more traffic compared to other available admission control schemes thereby guaranteeing high network utilization while maintaining the desired QoS.

***Index terms***—Admission Control, Rule-based Control, Traffic Estimation, Congestion Control

## A.INTRODUCTION

High-speed network supporting multimedia services have to be capable of handling bursty traffic and satisfying various QoS and bandwidth requirements. Asynchronous transfer mode (ATM), a high-speed network pipe, is one of the key technologies for integrating broad-band multimedia services (B-ISDN) in heterogeneous networks, where multimedia applications consisting of data, video and voice sources transmit information [4-5,8]. Due to broadband traffic pattern uncertainties and unpredictable statistical fluctuations in network traffic, the bandwidth management and traffic control in high-speed network pose new challenges and create difficulties. Therefore, a high-speed network must have an appropriate admission control (AC) scheme not only to maintain QoS for existing sources but also it should achieve high network utilization by properly admitting new traffic. In this paper, a novel admission controller scheme based on an adaptive methodology is proposed. The performance of the proposed scheme, though it is evaluated using cells, is applicable even for packet-based networks. For instance, an ATM provides services to the sources with different traffic characteristics by statistically multiplexing cells of fixed length packets of 53 bytes long. As a result, we have used packets/cells interchangeably.

Conventional AC schemes [6,9,10,12] that utilize either capacity estimation or buffer thresholds suffer from fundamental limitations such as the requirement of input traffic characteristics. A AC scheme must be dynamic in terms of regulating the traffic flows according to changing network conditions, however, requires understanding of network dynamics. Networks are forced to make decisions based on incomplete information, which not done properly degrades performance of the network. Therefore, a neuro-fuzzy approach for AC is proposed [2-3]. Though this approach appears to learn the uncertainity, but it is not clear whether the approach can be implemented in real-time, and further no mathematical analysis is provided in [2-3] to show its performance. While certain bandwidth estimation and allocation methods are heuristic [12] in nature, some using simulation [6], others that were proposed in the literature use neural and fuzzy logic [2-3].

Information on available bandwidth is required by the network to decide whether to accept a new source or not. This requires an accurate estimate of traffic conditions and the impact of adding a new source. Subsequently, this information is provided for calculating the amount of bandwidth currently allocated to accommodate existing sources, and by identifying how much additional bandwidth needs to be reserved on links over which a new traffic is to be routed. In order to obtain an accurate accounting of bandwidth currently used, the current traffic onto these links has to be determined.

Only estimating the bandwidth online will not suffice to admit new traffic. For an admission control scheme to perform reasonably, a congestion indicator has to be used to decide the impact of adding a new traffic source onto a network. In the literature, a number of congestion control schemes are proposed [5-6]. Unfortunately, many schemes are reactive in nature and they do not prevent congestion. Therefore, the novel predictive congestion control scheme in [12] is utilized to generate a congestion indicator and it is subsequently used in the admission controller.

A novel linear-in-the parameter (LIP) adaptive estimator is proposed. Tuning laws are provided for the estimator parameters and closed-loop convergence with network stability is proven using a Lyapunov-based analysis when an online bandwidth estimation scheme is deployed. Using the estimated traffic, buffered traffic and target QoS, the bandwidth required for all sources to meet a desired QoS is calculated. It is shown that the proposed online bandwidth estimation scheme guarantees the desired QoS by accurately estimating the bandwidth required by the existing sources even in the presence of bounded network traffic uncertainties. A new adaptive admission controller architecture is presented

[1] Research supported in part by the NSF ECS#9985739 and University of Texas Faculty Research Award #14-7519-01.
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in this paper that unifies the congestion controller, a bandwidth estimation scheme and the proposed rule-based controller. The performance of the adaptive admission controller is compared using service delay, cell/packet losses, and network utilization. Simulation results are provided to justify the theoretical conclusions.

## B. NETWORK MODEL

Figure 1 shows the popular end-to-end loop for evaluating the proposed admission control, bandwidth estimation and congestion control schemes [5] since the traffic enters at the ingress node/switch and leaves at the egress node passing through various networks/service providers and with very little information known about the internal network state. It is envisioned that the proposed admission controller resides at each network switch fabric where the link bandwidth usage at the ingress node is estimated at every measurement interval. The most important step in determining the bandwidth usage and allocation is to estimate the network traffic that is being accumulated at the ingress switch/node buffer in an intelligent manner using its occupancy.

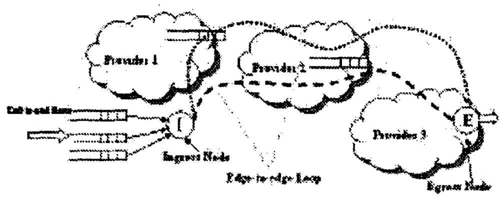

**Fig. 1:** End-to-end network loop.

Consider the buffer dynamics at an ingress node/switch fabric given in the following form

$$x(k+1)=f(x(k))+Tu(k)+d(k) \qquad (1)$$

with state $x(k)\in\Re^n$ being the buffer length (or occupancy) at time instant k, T being the measurement interval and $u(k)\in\Re^n$ being the source rate that is determined via feedback. The nonlinear function, $f(x(k))$, is a function of buffer occupancy, source rate, and service capacity, $S_r$, at the ingress switch/node, which is given as $sat[x(k)+(source\_rate(k)-S_r(k))T]$, where sat(.) is a saturation function. The unknown disturbance vector acting on the system at the instant k is $d(k)\in\Re^n$ is assumed to be bounded by a known constant, $\|d(k)\|\le d_M$. Here the disturbance vector $d(k)$ can be an unexpected traffic burst/load or change in available bandwidth due to the presence of a network fault. The state $x(k)$ is a positive scalar if a single switch/single buffer scenario is considered whereas it becomes a vector when multiple network switches/multiple buffers are involved. The first step in the proposed approach is to estimate the buffer occupancy using an estimate of the network traffic at the switch.

The objective here is to construct a model to identify the traffic accumulation at the switch as

$$\hat{x}(k+1)=\hat{f}(x(k))+Tu(k), \qquad (2)$$

where the state of the model, $\hat{x}(k)\in\Re^n$, being the buffer occupancy estimate at time instant k, with the nonlinear function $\hat{f}(x(k))$ being the traffic accumulation estimate. Define the performance criterion in terms of buffer occupancy estimation error as

$$e(k)=x(k)-\hat{x}(k), \qquad (3)$$

where the packet/cell losses, for a buffer size of $x_d$, are given by

$$c(k)=x(k)-x_d, \text{ if } c(k)>0, \quad = 0 \text{ Otherwise.} \qquad (4)$$

Equation (3) can be expressed using (1) and (3) as

$$e(k+1)=\tilde{f}(x(k))+d(k), \qquad (5)$$

where e(k+1) and x(k+1) denote the error in buffer occupancy and the buffer occupancy at the instant k+1 respectively, and the traffic flow modeling error is given by $\tilde{f}(x(k))=f(x(k))-\hat{f}(x(k))$. We ignore the sat(.) function since we won't allow the saturation of the buffer and therefore the sat(.) hereafter ignored.

Equation (5) calculates the packet/cell losses encountered at the switch fabric due to the traffic estimation scheme. In this paper, it is envisioned that by appropriately using an adaptive estimator in discrete-time to provide the traffic estimate, $\hat{f}(x(k))$, the error in buffer length, and hence the packet/cell losses can be minimized. The actual packet/cell losses are related to the bandwidth requirement for the next measurement interval. By appropriately combining the bandwidth estimated using the predicted traffic conditions, packet/cell losses, along with the queued data at the switch, one can estimate the bandwidth required to satisfy the target QoS in the next measurement interval. The buffer occupancy estimation error system expressed in (5) is used to focus on selecting discrete-time parameter tuning algorithms.

## C. ADAPTIVE TRAFFIC ESTIMATOR DESIGN

Assume, therefore, that there exist some constant ideal parameters $\theta$ for the ARMAX so that the nonlinear traffic accumulation function in (4) can be written as

$$f(x)=\theta^T\varphi(x(k))+\varepsilon(k), \qquad (6)$$

where $\varphi(x(k))$ is the regression matrix (function of buffer occupancy and its past values) at the switch and the approximation error $\|\varepsilon(k)\|\le\varepsilon_N$ with the bounding constant $\varepsilon_N$ known. Here the approximation error is selected so as to ensure the target CLR. For suitable approximation, it is necessary to select a large number of past values of buffer occupancy. But this number is selected here after carefully analysis as a trade off between computation and accuracy.

### C.1 Estimator Structure

Defining the adaptive traffic estimate by

$$\hat{f}(x(k))=\hat{\theta}^T(k)\varphi(x(k)), \qquad (7)$$

with $\hat{\theta}(k)$ is the current value of the parameters. It is presented in [8] that voice sources can be accurately modeled using the LIP approach. Further, it is shown that bursty MPEG data can be modeled as well with this approach [8]. In order to proceed, the buffer dynamics and the bandwidth estimation scheme are discussed first followed by the adaptive admission controller.

Let $\theta$ be the unknown ideal parameters required for the approximation to hold in (5) and assume they are bounded so that

$$\|\theta\| \le \theta_{\max}, \tag{8}$$

where $\theta_{\max}$ be the maximum bound on the unknown parameters. Then the error in the parameters during estimation is given by

$$\tilde{\theta}(k) = \theta - \hat{\theta}(k), \tag{9}$$

**Fact:** Since the buffer is of finite size, the past values of buffer occupancy are bounded by known positive values so that $\|\varphi(x(k))\| \le \varphi_{\max}$ and $\|\tilde{\varphi}(x(k))\| \le \tilde{\varphi}_{\max}$, where $\varphi_{\max}$ is the maximum buffer size.

Using the adaptive traffic estimate, the closed-loop buffer occupancy dynamics become

$$e(k+1) = \bar{e}_i(k) + \varepsilon(k) + d(k), \tag{10}$$

where the traffic flow modeling *error* is defined by

$$\bar{e}_i(k) = \tilde{\theta}^T(k)\varphi(x(k)). \tag{11}$$

**C.2 Parameter Updates for Guaranteed QoS**

It is required to demonstrate that the performance criterion in terms of cell losses, c(k), and latency monitored through buffer occupancy estimation error, $e(k)$, is suitably small and that the parameters $\hat{\theta}(k)$, remain bounded for then the traffic rate, $u(k)$, is bounded and finite.

**Theorem 3.1 (Traffic Estimator Design)** Let the desired buffer length, $x_d$, is finite. Also, let the traffic modeling error bound $\varepsilon_N$ and the disturbance bound $d_M$ are known constants. Take the parameter tuning provided by

$$\hat{\theta}(k+1) = \hat{\theta}(k) + \alpha\varphi(x(k))e^T(k+1), \tag{12}$$

with $\alpha > 0$ is a design parameter. Then the error in buffer occupancy,$e(k)$, and the parameter estimates $\hat{\theta}(k)$ are *UUB* provided the following conditions hold:

$$(1) \quad \alpha\|\varphi(x(k))\|^2 < 1, \tag{13}$$

$$(2) \quad c_0 < 1, \tag{14}$$

where $c_0$ is given by

$$c_0 = \frac{1}{(2 - \alpha\varphi^T(x(k))\varphi(x(k)))}. \tag{15}$$

**Proof:** See Appendix. ■

**D. AVAILABLE CAPACITY DETERMINATION**

Assume that all the packets/cells are transmitted at regularly spaced intervals to the buffer and consider that at the moment the new measurement interval starts, a new aggregate bandwidth value is being assigned. If the traffic that is being accumulated at the next measurement interval is known, then the additional bandwidth required meeting the target cell loss, delay and traffic can be determined as

$$\Delta Bw(k) = \max\left(\frac{\Delta\hat{f}(x(k))}{T}, \frac{\text{Actual Cell losses}}{TCLR * T}\right) + \frac{x(k)}{\tau}, \tag{16}$$

where $\Delta Bw(k)$ is the additional bandwidth required to process the new data, $\hat{f}(x(k))$ and $\hat{f}(x(k-1))$ are the traffic estimates at the instant k and k-1 respectively, $\tau$ being the target call transfer delay, and TCLR represents the target or desired packet/cell loss ratio. The bandwidth required for the next measurement interval is given by

$$Bw(k+1) = Bw(k) + \Delta Bw(k), \tag{17}$$

where $Bw(k+1)$, $Bw(k)$ represents the bandwidth at the time instant k+1 and k respectively. If Bw(k+1) exceeds $S_{\max}$, maximum capacity of the outgoing link, the available bandwidth is set to $S_{\max}$. Otherwise, the bandwidth is calculated by using (17).

In order to minimize short-term losses, the bandwidth of all the sources are adjusted using an apriori adhoc factor and the algorithm is referred to as over allocation algorithm. Here the factor $(0.8 \prec \rho \prec 1)$ is chosen a priori by trial and error and the bandwidth required is calculated as $\frac{BW(k)}{\rho}$ instead of $BW(k)$ at the time instant k.

**E. ADMISSION CONTROL**

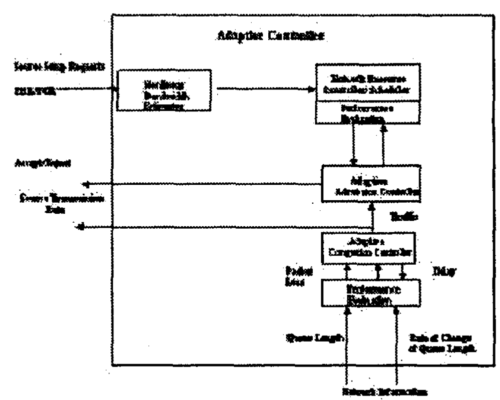

**Fig. 2**: Adaptive Admission Controller.

Here the available capacity (bandwidth), congestion indicator and buffer availability are utilized to admit new sources while maintaining QoS. Figure 2 shows an AAC with its peripheral schemes for multi-media high-speed networks. The AAC adopts three inputs: available capacity, available resource estimator, a congestion indicator, and a target packet/cell loss ratio and outputs a decision signal to indicate acceptance or rejection of the new source. The available capacity is the amount of available bandwidth at the next measurement interval, that is the current bandwidth used from existing sources subtracted from the maximum available bandwidth of the physical link.

$$\text{Available Capacity} = S_{\max} - \sum_{i=1}^{n} Bw_i(k), \tag{18}$$

where n is the number of existing sources. This available capacity is assumed to be available for admitting new sources. Other call admission control methods use equivalent-capacity-based algorithm. The equivalent-capacity-based algorithm transforms the traffic characteristics (usually described by three parameters: PCR, MCR, and peak cell duration) of a new source into a unified metric, referred to as the equivalent bandwidth, to reduce the dependence of the proposed control mechanism on the traffic type. However, the transformation is based on either a static relationship or simulation curves.

The congestion indicator provides an insight of the congestion in the transmission links based on the burtstiness of the existing traffic so that future congestion can be avoided when a new source is admitted. The packet/cell loss ratio (CLR) is the feedback provided by the system about its performance, which can be used to provide a closed-loop control system capable of adjusting itself to provide a stable and robust operation. Also, the available buffer space is used an input to the controller.

$$\text{Available\_network\_resources} = \varphi_{\max} - \sum_{i=1}^{n} x_i(k). \tag{19}$$

The network resource estimator keeps track of the available buffer space at each node/switch fabric. When a new source with a bandwidth specification is to be admitted, the available buffer space is updated by subtracting the assigned buffer space for the new source from the available network resource. Conversely, when an existing source ceases to transmit, the resource used by this source is now available to all other sources and hence the available network resource is updated.

The peripheral schemes for the AC are a congestion controller [11], a bandwidth estimator as presented in Sections B through D, and a network resource estimator. The congestion controller generates a congestion indicator according to the measured system statistics, such as the queue length q(k) and its past values, the cell loss ratio (CLR), and round trip delays at the egress node. Here the predictive congestion controller developed in [11] is preferred but any congestion controller including buffer threshold can be used. The congestion indicator flag is set when the past several buffer occupancy values are about 90 percent full, the rate of change of the queue length is positive and high, the round trip delays are large, as well as the CLR occurs consistently. These values are obtained from careful analysis. In other words,

If ((q(k)) > 90%) and (q(k-1) > 90%) and (RTT $> 2RTT_{\min}$)) then congestion_flag = true, else false. (20)

Bandwidth estimator obtains an accurate estimate of the current bandwidth that to be assigned for the next measurement interval. Initially, the new source has to provide its intended PCR only whereas, other schemes request mean cell rate (MCR), burstiness, delay, and number of packets/cells in addition to PCR. All admitted new sources are assigned an initial bandwidth value equal to the PCR. From the next measurement interval onwards, the bandwidth to be assigned for this new source after its admission into the network is calculated using (17).

Therefore the approach presented in this paper is more adaptive and does guarantee the performance interms of QoS and network utilization. Based on the information, and to make the proposed admission controller simple and easy to implement, rules are generated as follows:

If (congestion flag is true) and (available_capacity > PCR) and (Available_network_resources > 10%) then admit source 'i' else reject. (21)

The sources are expected to return to wait state, which is typically a very small value, and they are allowed to send a request again for admission into the network after the wait state. At each measurement interval, the congestion controller generates the transmission rates for all the sources to meet the QoS. Here the congestion controller operates at the packet level whereas the admission controller works at the source level. These two controllers operate at two time scales and their interaction has to be carefully studied to avoid any instability and performance deterioration. Future work is to use hybrid system theoretic-approach for designing admission controllers.

## F. SIMULATION RESULTS

In our admission control example, we drive the sources independently with both voice (ON/OFF) and video (MPEG) data.

### F.1 Adaptive Estimator Model

Past six values of the buffer occupancy were used as inputs to the LIP model. Since the number of inputs to the ARMAX model at each switch is 6 and the output is a single value, the parameter vector $\hat{\theta}(k)$ is a 6 by 1 vector for each switch. The initial adaptation gain, $\alpha$, is taken as 0.1. The buffer occupancy for both the switches are considered empty initially. The initial parameter estimates are chosen as $\hat{\theta}(1)=[0\ 0\ 0\ 0\ 0\ 0]^T$ for each switch. However one can select any initial values for the parameters. The parameter tuning updates derived herein were deployed for the simulation. The network model and the traffic sources used in the simulations are discussed next.

### F.2 Network Model

The network model used in simulations is similar to that shown in Figures 1. In the simulations, two-switch scenario is considered. Four MPEG sources are assumed to be transmitting at Switch 1. The output of Switch 1 is connected to Switch 2. In addition, Switch 2 is also allowing 4 MPEG sources. Initially, it is assumed that the physically available bandwidth at both switches is equal to the PCR of all the sources. Four sources are to be admitted at Switch 1 and 4 are to be admitted at Switch 2. In addition, at 3000 units of time, the output of Switch 1 is admitted at Switch 2.

The PCR of the four sources combined at Switch 1 is 13200 cells/sec whereas the PCR of the three admitted MPEG sources are 9150, 9100, 9040 cells/sec respectively whereas the PCR of the two ON/OFF sources are 4800 and 4800 respectively. The PCR of the data from Switch 1 that is admitted at Switch 2 is 137000 cells/sec. Both the switch fabrics in this case are considered as ingress nodes but Switch 2 is considered as Egress node for several sources sending traffic through Switch 1. The admission condition will be checked every 500 frame time, and if the conditions are met a source will be admitted at that instant, otherwise it is rejected.

The target transfer delay is defined as 0.1% of the total time to transmit the data if the bandwidth is available at the peak cell rate. This value is given as 167 msec (0.1% of 167sec) and it is used as the target cell transfer delay.

**F.3 Simulation Examples**

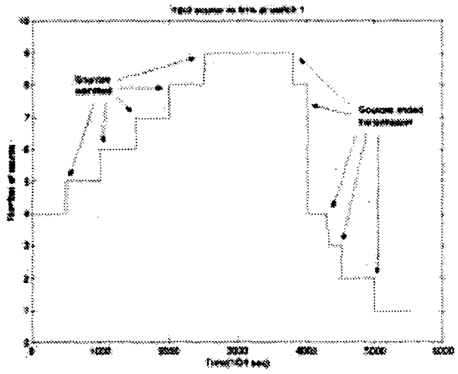

**Fig. 3**: Sources Admitted at Switch 1.

Three methods will be compared: The first method assigns bandwidth using the PCR of the source. The second method presents an adaptive LIP algorithm for estimating the traffic and then calculates the available capacity. However, in the case of adaptive with over allocation algorithm, the over allocation factor $\rho$ is taken as 0.95. In the examples, the exponential weight moving average (EWMA) filter was applied on the bandwidth error for convenience and readability. Note that a positive error value implies that not enough bandwidth is assigned (bandwidth is not estimated accurately) whereas a negative error value implies that the assigned bandwidth is not fully utilized. Figure 3 shows the number of admitted sources at switch 1 when the physically available bandwidth is equal to the PCR of all the sources. Figure 4 shows the corresponding plot for Switch 2. Here all source are admitted with no service and transmission delays or losses.

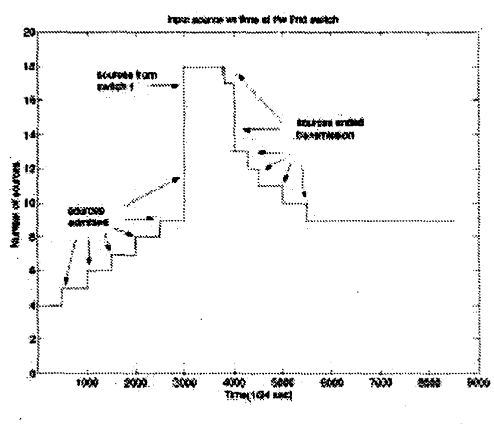

**Fig. 4**: Sources admitted at Switch 2.

The bandwidth estimation algorithm and the ARMAX-based AC are used to admit the traffic. The bandwidth prediction error at the switches is shown in Figures 5 and 6. When the physically available bandwidth is equal to PCR of the all sources, then all sources are admitted irrespective of the method used. However, large amount of bandwidth is wasted when PCR-based scheme is used. Though a small prediction error similar is observed, the selection of over allocation factor is done by trial and error whereas adaptive scheme generates a small error.

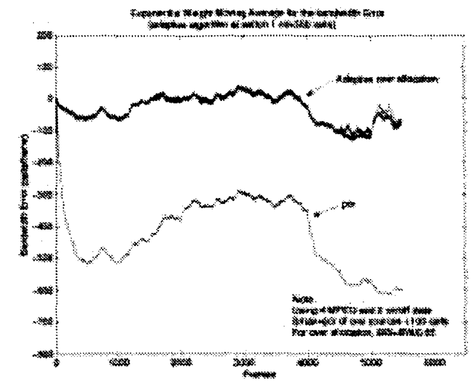

**Fig. 5**: Prediction Error at Switch 1.

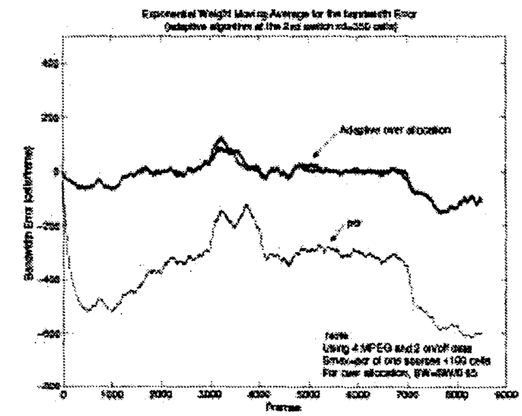

**Fig. 6**: Prediction Error at Switch 2.

When the available bandwidth is not equal to the PCR of all sources, several new sources are rejected by the other methods whereas our adaptive method admitted more sources resulting in high network utilization due to accurate bandwidth estimation. Figure 7 show the comparison between the available bandwidth being PCR and PCR of one ON/OFF source at Switch 2. As expected, fewer sources are admitted. The CLR for adaptive scheme is slightly higher than adaptive with over allocation and the PCR since the adaptive scheme is conservative; however the CLR meets the target specification. The CLR resulting from PCR is near zero as enough resources are a priori reserved. These results clearly show that the bandwidth assignment has to be accurate for admitting new sources.

## G. CONCLUSIONS

This paper proposes a LIP-based online adaptive bandwidth estimation, allocation and call admission control scheme for high-speed networks that support multimedia. The network buffer dynamics is modeled as a nonlinear dynamical system and an LIP adaptive algorithm is designed to estimate the traffic flow. This adaptive approach does not require the information about the network system dynamics nor traffic rate accurately. In fact, the proposed adaptive estimator guarantees performance as shown through the Lyapunov analysis. The bandwidth required to meet the QoS is then estimated and the available capacity is derived given the actual cell losses, latency and the estimated traffic flow. This information along with the intended PCR of the source to be admitted, predictive congestion indicator and desired QoS metrics are used to construct the adaptive admission controller. Results are presented to evaluate the performance of the proposed approach with ON/OFF and bursty MPEG data. Based on the results, it was concluded that the proposed methodology generates an accurate estimation of bandwidth required and that to be assigned to the sources to meet the QoS. Accurately estimating the bandwidth along with the rules for admission of network traffic results in high network utilization.

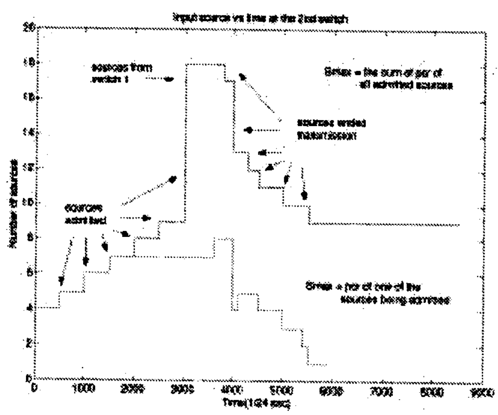

**Fig. 7:** Admission controller performance.

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## APPENDIX

***Proof:*** *Define the Lyapunov function candidate*

$$J = e^T(k)e(k) + \frac{1}{\alpha} tr\left(\tilde{\theta}^T(k)\tilde{\theta}(k)\right) \tag{A.1}$$

*the first difference is given by*

$$\Delta J = e^T(k+1)e(k+1) - e^T(k)e(k) + \frac{1}{\alpha} tr\left(\tilde{\theta}^T(k+1)\tilde{\theta}(k+1) - \tilde{\theta}^T(k)\tilde{\theta}(k)\right) \tag{A.2}$$

*Use the buffer length error dynamics (10) and tuning mechanism (12) to obtain*

$$\Delta J = -[1-c_0]\left(\|e(k)\|^2 - \frac{c_2}{(1-c_0)}\right) - \left[1-\alpha\varphi^T(x(k))\varphi(x(k))\right] \left\| e_i(k) - \frac{\left(\alpha\varphi^T(x(k))\varphi(x(k))\delta(k)\right)}{\left(1-\alpha\varphi^T(x(k))\varphi(x(k))\right)} \right\|^2 , \tag{A.3}$$

where $\delta_{\max} = \varepsilon_N + d_M$ , and $c_2 = \dfrac{\delta_{\max}^2}{(1-\alpha\varphi_{\max}^2)}$. (A.4)

*Since* $c_0$ *and* $c_1$ *are positive constants,* $\Delta J \le 0$ *as long as the conditions in (13) and (14) are satisfied and with the upper bound on the buffer occupancy estimation error by*

$$\|e(k)\| > \left[\sqrt{\frac{c_2}{(1-c_0)}}\right] \tag{A.5}$$

In general $\Delta J \le 0$ in a compact set as long as (13) and (14) are satisfied. This demonstrates [1] that the buffer occupancy error is UUB. To show the parameters are bounded, consider the dynamics relative to the errors in the parameter estimates are given by

$$\tilde{\theta}(k+1) = (1-\alpha\varphi(x(k))\varphi(x(k))^T)\tilde{\theta}(k) - \alpha\varphi(x(k))(\varepsilon+d)^T , \tag{A.6}$$

where the buffer occupancy estimation error is considered bounded. Applying the persistence of excitation condition [1], and noting that the traffic modeling error and disturbance are bounded, the boundedness of $\tilde{\theta}(k)$ implies that the parameter estimates $\hat{\theta}(k)$ are bounded. ■