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Stochastic Estimator-Based Wireless Traffic Control Schemes

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Abstract: Recent works on Available Bit Rate (ABR) traffic control have generated efficient control schemes for ABR traffic on Asynchronous Transfer Mode (ATM) network. This study examines the improved performance envisaged if these control schemes adjust dynamically to the varying ABR bandwidth capacity in a stochastic manner instead of conventional deterministic approach .The performance difference between setting explicit rate deterministically for transmitting ABR sources and doing the same stochastically using a learning automaton is of particular interest. The learning automaton used is the Stochastic Estimator Learning Automaton (SELA). The performance difference is measured by comparing the congestion levels of the SELA-based control scheme with the reference deterministic control mechanism. Simulation results show that the stochastic estimator gives a better performance. The higher average congestion level experienced by the conventional deterministic approach is mainly due to the propagation time delay in the closed-loop feedback control schemes.

Key words: Learning algorithm and training, network, application control, deterministic, estimation, performance evaluation, simulation, network architecture, feedback control, propagation-time, stochastic control, random sampling, equation, reinforcement learning, convergence time, robust

INTRODUCTION

A challenging task of network technologies in the last decade has been to integrate multiple types of service over a single network. The Broadband Integrated Services Digital Network (B-ISDN), which is recently being vigorously researched and developed all over the world, is the telecommunication technology developed in the late 1980s that would be capable of adequately transporting data of all current and future applications at speeds typically in excess of 150 Mbps. This telecommunication technology requires a network architecture that can handle the differing requirement of these types of services and adapt to meet the Quality of Service (QoS) metrics required by each type of network traffic.

ATM technology, which promises to provide this type of adaptable network by providing flexible access to network while still guaranteeing specific QoS parameters, has been adopted by International Tele communication Union-Telecommunication (ITU-T) as a transport, multiplexing, and switching technology for B-ISDN[1,2]. The ability of the ATM technology to meet the adaptation requirement is attributed to the switching technology it adopts[3], called cell switching. The ATM cell is a fixed-length (53 octets) packet that constitutes every form of user information ranging from 64Kbps voice to several 100Mbps data. A key benefit of ATM is that it has in-built support for a diverse range of QoS categories. Within the ATM layer, the ATM Forum currently identifies five different classes[4], although the proposed version of the Traffic Management specification[5], includes a further service class known as guaranteed frame rate. These existing classes are stated below.

Constant bit-rate (CBR) service category is typically used by connections that require a static amount of bandwidth that is continuously available during the connection life's time. It is a deterministic service designed to support real-time applications requiring tightly constrained delay variations, minimal cell loss, and cell delay; such as circuit emulation, non-compressed voice traffic and continuous bit-rate video.

Variable bit-rate real time (VBR-rt) provides tightly constrained delay and delay variation for applications such as video and voice with silence

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removed. Variable bit-rate non-real time (VBR-nrt), is similar to VBR-rt except there are no delay bounds associated with this service category.

Unspecified bit-rate (UBR) is intended for non-real time applications such as file transfer and e-mail where the service provides best-effort delivery but offers no traffic-related guarantees. For a UBR connection, the peak transmission rate can be high, i.e., up to the maximum peak cell rate (PCR) value supported by a link, but the potential cell loss rate can also be high, resulting in a relatively low useful throughput for the UBR service.

Available bit-rate (ABR) is designed to support highly bursty non-real-time applications that are able to modify their data transfer rate dynamically during the life time of the connection according to network conditions whilst maintaining well-defined cell loss constraints. These elastic traffic services allow the network to operate at high utilization without undue risk of congestion, whilst exploiting transitory spare capacity for a relatively low tariff.

This dynamic adaptability of source transmission rate based on the available network resources is only possible if information of the current network status is returned to the source. Consequently, the approach chosen by the ATM Forum as the best match for the goals of ABR service is to control the transmission rate of connections directly: i.e., rate-based traffic flow control[6].

However, for feedback control schemes, the propagation time-delays incurred in the feedback path and the temporal variation in the link capacity are considered to be problematic features. Therefore, successful ABR source-rate control will depend on the effectiveness of the controller to overcome these delays and to adapt to the temporal variation in the excess bandwidth[7].

This work examines the effect of propagation time-delay on the performance of feedback traffic control schemes for ABR service that compute source rates (Explicit Rates) using deterministic approach. The possibility of a better performance using stochastic approach is the focus of this work. The learning automaton used is the SELA. The remaining study is structured as subsequently described. Section 2 details an overview of ABR traffic features and ABR traffic control mechanisms. The model of SELA is given in section 3 while section 4 presents simulation results. Finally, section 5 summarizes the work.

TRAFFIC CONTROL MECHANISM

ABR is the ATM layer service category that allows the ATM layer transfer characteristics provided by the network (i.e., throughput) to alter, subsequent to connection establishment so that real-time bursty data applications can be transported reliably. It is expected that a user that adapts its traffic to the changing network throughput, as indicated by feedback control information received from the network, will experience a 'low' cell loss ratio (CLR) while cell transfer delay (CTD) and cell delay variation (CDV) are not controlled for ABR connections. The ABR service category is thus not intended to support real-time applications. Although the CLR is the only QoS parameter that is tightly constrained, the CTD and CDV are to be catered for reasonably, by the network.

The bandwidth made available to an ABR connection on a particular link by the network may vary between the MCR (Minimum Cell Rate) and the PCR (Peak Cell Rate)-ABR connection source parameters-for some reasons. Amongst this is that, bandwidth resources are being reserved for CBR and VBR connections that are set up. Secondly, bandwidth becomes free again when CBR and VBR connections are released. Besides, non-reserved bandwidths made available to other ABR connections sharing that same link possibly remain unused.

The conformance of an SES (Source End System)-the originating part of the connection as defined by the ATM Forum-to negotiate traffic contract is monitored by a policy algorithm called Generic Cell Rate Algorithm (GCRA) The SES is thus not supposed to send cells at a rate that exceeds the PCR, according to the GCRA conformance definition GCRA (1/PCR, τ_p).

Conversely, it is expected that a network shall never force the SES to a rate below the MCR. If the SES were to disregard the network feedback control information, cells sent in accordance with the GCRA (1/MCR, τ_m) would be identified as conforming.

The ATM Forum adopted a rate-based, as opposed to a credit-based approach with buffer allocation, closed-loop traffic control mechanism for ABR service category. This control mechanism will allow the SES to dynamically adjust its cell-sending rate based on feedback control information received from the network, indicating its availability status of bandwidth resources.

To establish an ABR connection, the SES creates a connection with a call set-up request. During this call set-up phase, the values of a set of ABR-specific parameters are identified. Some values are requested by the source and possibly modified by the network (e.g., PCR and MCR); while others are directly chosen by the network (e.g., the parameters characterizing the process for dynamically updating rates, such as Additive Increase to Rate (AIR), Number of Cells/RM (Nrm-1), or Rate Decrease Factor (RDF).

Once the source has received permission, it begins cell transmission. Transmission is initiated by the injection of Resource Management (RM) cells into its information cell stream on a regular basis, in order to probe the network as regards its available bandwidth resources, followed by data cells. The SES continues to send RM cell after every Nrm-1 user cells transmitted. These RM cells are standardized by the ITU-T to have CLP bit set to zero and are identified by an ATM loader Payload Type Identifier (PTI) equal to 110 i.e., 6, for a virtual channel connection.

The virtual channel identifier and the PTI are equal to 6 and 110 respectively for RM cells referring to a virtual path connection. Subsequently, for an ABR traffic control mechanism, that operates on a pure end-to-end basis, these SES-originating RM cells are then returned by the DES (Destination End System-the destination part of the connection), thereby formally closing the information control loop back towards the SES. Thus for the ABR information flow from the SES to the DES, there exists two RM cell flows: one in the forward direction from SES to DES and the other in the backward direction from DES to SES. The direction of flow to which an RM cell belongs will be indicated by means of one bit direction indicator (DIR), in the RM cell's information field.

In order to maintain tight control over ABR traffic flow in an ATM network, provisions for nodes to act as virtual end systems are made. This concept allows the information control loop to be potentially segmented at any convenient point along the end-to-end path. Despite the 'positive' feedback concepts employed by most conventional ABR traffic control schemes, the set rates (Explicit Rate) for the SES contained in the RM cell sent by the DES computed based on deterministic instantaneous bandwidth available suffer some drawbacks in performance due to feedback propagation-time delays. The following subsections discuss further refinement that have made to the basic explicit rate scheme of ABR.

Explicit rate feedback schemes: The basic explicit rate feedback scheme has three clear advantages over explicit forward congestion indicator (EFCI) control scheme and these are:

- Policing is straightforward
- Given the fast convergence time, initial rates are not as important
- The scheme is robust against errors in or loss of RM cells

The Enhanced EFCI control scheme was proposed and stands as a refinement made to the basic explicit rate scheme of ABR flow control. This scheme used queue growth rate in place of queue length as a measurement of congestion, and it was discovered that it results in fairer treatment of sources that start up relatively late.

Target utilization band (TUB) scheme has high throughputs and short delays due to small average queue lengths. .A strong attraction to this scheme is the fact that sources within the network reach steady-state 10 to 20 times faster than under enhanced proportional rate control algorithm EPRCA. The Explicit Rate Indication for Congestion Avoidance (ERICA) is more aggressive variation of the TUB control scheme. This control scheme allows a source to increase the rate across an under-loaded VC to its fair share regardless of network condition. It also allows a VC at or above fair share to receive an increased rate if the link as a whole is being underused. The Congestion Avoidance using Proportional Control (CAPC) key feature is that it provides oscillation-free performance when the system is at steady state[8].

There were various attempts made by various authors to improve and enhance the control schemes discussed so far and here are some of them.

Virtual sources and destinations: This setup would create smaller feedback loops, and thus faster response time. Each segment would be allowed to use any available congestion control scheme The downside is that a switch within this arrangement referred to as a VSVD switch, needs to main a queue for each VC, which adds considerable expense.

The multicast VCs scheme can be extended to work for point-to-multipoint (P2MP) as long branch traffic conforms to the expected behavior for a P2P connections. Priority congestion control scheme for Wide-Area ATM networks can be improved if priority is given to existing traffic, relative to data entering the network, via a network access control scheme. The Interoperability of EFCI and ER switch. Experiments have demonstrated that each an EFCI switch is replaced by an ER switch within a particular ATM network, performance-throughput and fairness of bandwidth allocation improves to a measurable extent[8].

THE SELA APPROACH

SELA is a reinforcement-learning algorithm that utilizes a stochastic estimator and can operate in non-stationary environment with high accuracy and high adaptation rate[8]. SELA, like other learning automaton, interacts with a stochastic environment and tries to learn the optimal action offered by the environment, via a learning process.

The automaton chooses one of the offered actions according to a probability vector, which at every instant contains the probability of choosing each action. The chosen action triggers the environment that responses with a feedback dependent on the stochastic characteristic (mean reward or reward probability) of the chosen action. It takes into account this answer and modifies its state by means of a transition function. The new state of the automaton corresponds to a new probability vector given by a function, called output function. The action that has the maximum mean reward are learnt ultimately and chosen more frequently than the other actions by the learning automaton.

In SELA scheme, the estimates of the mean rewards of actions are computed stochastically. So, they are not strictly dependent to the environmental responses. The dependence between the stochastic estimates and the deterministic estimator's content is more relaxed if the latter are un-updated and probably invalid. Thus, the estimator is always recently updated and, consequently, able to adapt to environmental changes such as ABR bandwidth.

The SELA learning automaton is defined as a sextuple <A, B, P, T, G, E> where:

A = $\{a_1, a_2,...,a_r\}$ is the set of the r actions offered by the environment

B = (0, 1) is the input set of possible environmental responses. The environmental response can take any value in the (0, 1) space

Q = is the set of the possible internal states of the automaton. Since there is a one-to-one relation (G) between the automaton's states and the actions, the state Q can be omitted from the sextuple. However, for reasons of completeness we include Q in the formal definition of SELA learning automaton.

P = is the probability distribution over the set of actions. We have: $P(t) = \{P_1(t), P_2(t),..., P_r(t)\}$ where $P_i(t)$ is the probability of selecting action a $\in$ A at time instant t_i

G = Q = A is the output function. As noted before, G is a deterministic one-to-one function.

E = is the estimator that, at any time instant, contains the estimated environmental characteristics

We define:

$$E(t) = (D'(t), M(t), U(t)) \quad (1)$$

Where:

- $D'(t) = \{d'_1(t), d'_2(t), ...d'_r(t)\}$ is the Deterministic Estimator Vector which, at any instant t, contains the current deterministic estimates of the mean rewards of the actions. The current deterministic estimate $d'_i(t)$ of the mean reward of action a_i is defined as follows:
- $d'_I(t)$ = (The total reward received by the automaton during the last W times that action a_i was selected)/W. W is an integer internal automaton's parameter called learning window, (Vasilakos and Papadimitriou, 1990)
- $M(t) = \{m_1(t), m_2(t), m_r(t)\}$ is the Oldness Vector which, at any time instant t, contains the time passed from the last time each action was selected. Thus, for every action a_i we define:

- $m_i(t) = t\text{-}\max\{j: j<t \text{ and } a(j) = a_i\}$
- $U(t) = \{u_1(t), u_2(t), u_r(t)\}$ is the Stochastic Estimator Vector which, at any time instant t, contains the current stochastic estimates of the rewards of the actions. The current stochastic estimate $u_i(t)$ of the mean reward of action a_i is defined as:

$$u_i(t) = d'i(t) + N(0, oi2(t)) \quad (2)$$

T = is the learning algorithm

The specification of T constitutes the design of the automaton. Its algorithmic description is presented below:

Initialization: All $P_i = 1/r$.

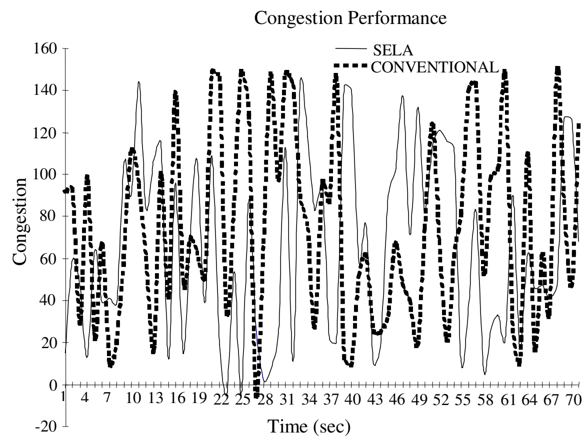
Step 1: Select an action $a(t) = a_k$ according to the probability vector

Step 2: Receive the feedback $b(t) \in (0, 1)$ from the environment

Step 3: Compute the new deterministic estimate $d'_k(t)$ of the mean reward of action a_k as it is given by equation 1 above

Table 1: Average congestion values for the conventional and SELA approaches

	Congestion values												Cum. Avg.
SELA	39.4	83.8	69	53.8	24.2	93.6	76.4	71.2	113	33	47.4	81.8	
Conventional	67	60.2	69	88.6	97.6	96.2	61.4	39.4	61.4	103.4	62.2	88.6	
Cogest_Diff.	27.6	-23.6	0	34.8	73.4	2.6	-15	-31.8	-51.6	70.4	14.8	6.8	9.0333333
SELA	93.6	82.2	75.4	80	44.6	48	101.8	93.4	39.4	99.8	98.6	71.6	
Conventional	84.6	32.4	63	63.2	61.4	66.6	55.4	80.4	94.6	77.2	78.4	84.4	
Cogest_Diff.	-9	-49.8	-12.4	-16.8	16.8	18.6	-46.4	-13	55.2	-22.6	-20.2	12.8	-7.2333333
SELA	68.8	99	26.8	50.8	84.6	43.6	41.8	74.2	79	81.2	66	89.4	
Conventional	57	77.6	43.8	83.6	82.2	37	66.6	88.8	27.2	61.2	75.2	64.4	
Cogest_Diff.	-11.8	-21.4	17	32.8	-2.4	-6.6	24.8	14.6	-51.8	-20	9.2	-25	-3.3833333
SELA	62.6	65	41.4	73.6	65.4	78.2	54	52.8	93.6	55.8	58.6	53.6	
Conventional	71.8	76.8	118.8	66.6	60.2	86	60	51.6	55.4	47	66.6	82.2	
Cogest_Diff.	9.2	11.8	77.4	-7	-5.2	7.8	6	-1.2	-38.2	-8.8	8	28.6	7.3666667
SELA	82.4	108.2	37.6	49.8	26.8	55	76	47.8	83.8	66.8	28	60.2	
Conventional	26	84.6	79.2	56.6	77.4	87.8	67.4	57.4	78.6	55.2	62	71.2	
Cogest_Diff.	-56.4	-23.6	41.6	6.8	50.6	32.8	-8.6	9.6	-5.2	-11.6	34	11	6.75



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Step 4: Update the Oldness Vector by setting m_k (t) = 0 and m_i (t) = m(t-1) + 1 for every i = k

Step 5: For every action a_i (i = 1, 2...r) compute the new stochastic estimate $u_i(t)$ as it is given by equation 2

Step 6: Select the optimal action a_m that has the highest stochastic estimate of mean reward. Thus $u_m = \max\{u_i\ (t)\}$

Step 7: Update the probability vector

Step 8: Go to step 1

This approach is proposed to have a better performance when adopted in highly stochastic ABR bandwidth environment. The estimating technique employed by SELA enables a better ABR bandwidth estimation at every instant that an RM cell is sent, since the propagation time is optimally utilized as a learning period.

SIMULATION RESULTS

The conventional deterministic control scheme and the proposed SELA-based counterpart were simulated. Equal ABR-specific parameters were used for the two systems. The performance parameter evaluated is the level of congestion that results for the two approaches. The average differences between the two resulting congestion levels were also computed to enable a cumulative evaluation of the systems. The ABR-specific parameters used in the simulation, which were randomly generated, are similar for both approaches. As shown in Fig. 1, the congestion levels for both approaches are evaluated after every second. A positive congestion value connotes a demand beyond the available network resources-i.e., congestion. However, a negative value implies an under-utilization of available network resources. On the average, as shown in Table 1, the SELA approach gives a lower cumulative congestion level, which indicates that less of congestion of the network resources occurs using this approach. The net area occupied by the graph for SELA approach also supports this fact.

CONCLUSION

The conventional approach of most ABR traffic control schemes, that is, deterministic computation of Explicit Rates for transmitting sources has been investigated and evaluated. The propagation delay incurred in these control schemes due to feedback has been confirmed to have notable effect on their performance. A newly proposed approach using a stochastic estimator as the basis of the explicit rate computation has also been studied and evaluated. This approach however proves a better performance. The cumulative average congestion level, which is the basis for the basis for the performance evaluation this approach, is lower.

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