On the Use of Stochastic Estimator Learning Automata for Dynamic Channel Allocation in Broadcast Networks

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Abstract - Due to its fixed assignment nature, the well-known TDMA protocol suffers from poor performance when the offered traffic is bursty. In this paper, a new time division multiple access protocol which is capable of operating efficiently under bursty traffic conditions is introduced. According to the proposed protocol, the station which grants permission to transmit at each time slot is selected by means of stochastic estimator learning automata. The system which consists of the automata and the network is analyzed and it is proved that the probability of selecting an idle station asymptotically tends to be minimized. Therefore, the number of idle slots is drastically reduced and consequently, the network throughput is improved. Furthermore, due the use of a stochastic estimator, the automata are capable of being rapidly adapted to the sharp changes of the dynamic bursty traffic environment. Extensive simulation results are presented which indicate that the proposed protocol achieves a significantly higher performance than other well-known time division multiple access protocols when operating under bursty traffic conditions.

1 Introduction

Channel allocation is a key issue in broadcast networks. A significant number of multiaccess protocols have been proposed as solutions to this problem.

Demand Assignment protocols - such as Token Ring, Token Bus and DQDB [1],[2] - are based on a signaling procedure which allows certain network entities to be informed about the transmission and networking needs and demands of the network stations.

Random Access protocols - such as ALOHA, CSMA and CSMA/CD [1],[2] - are characterized by the fact that stations contend for access to the communications channel, in accordance with an algorithm that can lead to colliding transmissions. All the collided packets are scheduled for retransmission.

Fixed Assignment protocols - such as TDMA [2]-[8], RTDMA [9], [10] and FDMA [1] - assign a fixed portion of the available bandwidth to each station. In this way, collisions are avoided. Due to the absence of collisions, protocols of this family achieve a high performance when the traffic of each station is stable and a priori known. However, when the traffic is bursty, fixed assignment protocols are not capable of being adapted to the sharp changes of the stations' traffic. Therefore, their performance is dramatically degraded.

In this paper, a new multiple access protocol which is capable of operating efficiently under bursty traffic conditions is introduced. According to the proposed protocol, the station which grants permission to transmit at each time slot is selected by means of learning automata [11]-[16].

The system which consists of the automata and the network is analyzed and it is proved that the probability of selecting an idle station asymptotically tends to be minimized. Therefore, the number of idle slots is drastically reduced and consequently, the network throughput is improved. Furthermore, due the use of a stochastic estimator [16], the automata are capable of being rapidly adapted to the sharp changes of the dynamic bursty traffic environment.

The proposed Stochastic-Estimator-based Time Division Multiple Access (SE-TDMA) protocol is applicable to a broad range of broadcast network architectures, including bus, star and wireless LANs. This paper focuses on the theoretical aspects of SE-TDMA rather than on its application to specific network architectures.

The paper is organized as follows: In Section 2, the Stochastic Estimator Learning Automaton is presented, while the proposed SE-TDMA protocol is introduced in Section 3. In Section 4, extensive simulation results are presented which indicate the superiority of the SE-TDMA protocol over other well-known TDMA protocols. Finally, concluding remarks are given in Section 5.

2 The Stochastic Estimator Learning Automaton

The Stochastic Estimator Learning Automaton (SELA)

0-7803-6375-2/00/$10.00

[16] is a learning automaton which keeps estimates of the environmental characteristics in order to achieve an accurate convergence. The estimates of the reward probabilities of actions are computed stochastically. So, they are not strictly dependent on the environmental responses. The dependence between the stochastic estimates and the deterministic estimator's contents is more relaxed when the latter are old and probably invalid. In this way, actions that have not been selected recently, have the opportunity to be estimated as "optimal", to increase their choice probability, and, consequently, to be selected. Thus, the automaton is capable of being adapted to the environmental changes, since the estimator is always recently updated.

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

$A = \{a_1, \ldots, a_r\}$ is the set of the r offered actions ($2 \leq r < \infty$). The action selected at time instant t is denoted by $a(t)$.

$B = \{0, 1\}$ is the input set of the possible environmental responses. "1" denotes a reward and "0" denotes a penalty response. The environmental response at time instant t is denoted by $b(t)$.

P is a probability distribution over the set of actions. We have: $P(t) = \{p_1(t), \ldots, p_r(t)\}$, where $p_i(t)$ is the probability of selecting action a_i at time instant t.

E is the Estimator, which at any time instant t, contains the estimated environmental characteristics. We define: $E(t) = (D'(t), M(t), G(t))$ where:

$D'(t) = \{d'_1(t), \ldots, d'_r(t)\}$ is the Deterministic Estimator Vector, which, at any time instant t, contains the current deterministic estimates of the reward probabilities of actions. The deterministic estimate $d'_i(t)$ of the reward probability of each action a_i ($i = 1, \ldots, r$) is defined as follows:

$$d'_i(t) = \frac{\sum_{k=1}^{W} w_i^k(t)}{W} \quad (1)$$

where: W is an integer internal parameter of the automaton called "learning window" and $w_i^k(t)$ for $k = 1, \ldots, W$ are the environmental responses received during the W last times that action a_i was selected.

$M(t) = \{m_1(t), \ldots, m_r(t)\}$ is the Oldness Vector, which at any time instant t contains the time passed from the last time each action was selected. Time is counted in number of iterations. We define: $m_i(t) = t - \max_\tau \{\tau : \tau \leq t \text{ and } a(\tau) = a_i\}$.

$G(t) = \{g_1(t), \ldots, g_r(t)\}$ is the Stochastic Estimator Vector, which, at any time instant t, contains the current stochastic estimates of the reward probabilities of the actions. The current stochastic estimate $g_i(t)$ of each action a_i is defined as follows:

$$g_i(t) = d'_i(t) + N(0, \sigma_i^2(t)) \quad (2)$$
$$where: \quad \sigma_i(t) = min\{am_i(t), \sigma_{max}\}$$

$N(0, \sigma_i^2(t))$ denotes a random number selected with a normal probability distribution, with zero mean and a variance equal to $\sigma_i^2(t)$. a is an internal automaton's parameter that determines how rapidly the stochastic estimates become independent from the deterministic ones. σ_{max} is the maximum permitted value of $\sigma_i(t)$. It bounds the stochastic estimates in order not to increase infinitely.

T is the learning algorithm. Its algorithmic description is presented below:

STEP 1: Select an action $a(t) = a_k$ according to the probability distribution $P(t)$.

STEP 2: Receive the feedback $b(t) \in \{0, 1\}$ from the environment.

STEP 3: Compute the deterministic estimate $d'_k(t)$ of the reward probability of action a_k, as it is given by relation (1).

STEP 4: Update the oldness vector by setting $m_k(t) = 0$ and $m_i(t) := m_i(t-1) + 1$ for all $i \neq k$.

STEP 5: For each action a_i (for $i = 1, \ldots, r$) compute the new stochastic estimate $g_i(t)$, as it is given by relation (2).

STEP 6: Select the "optimal" action a_m that has the highest stochastic estimate of reward probability. Thus, $g_m(t) = \max_i\{g_i(t)\}$.

STEP 7: Update the probability vector in the following way:
i) For every action a_i with $i \neq m$ and $p_i(t) \geq \frac{1}{n}$, set:
$p_i(t+1) := p_i(t) - \frac{1}{n}$.
(n is the "resolution parameter" of the automaton which determines the step size of the probability updating.)
ii) For the "optimal" action a_m set:
$p_m(t+1) := 1 - \sum_{i \neq m} p_i(t+1)$.

STEP 8: Go to step 1.

3 The SE-TDMA Protocol

According to the SE-TDMA protocol, all the stations are provided with a SELA learning automaton which decides which station grants permission to transmit at each time slot. All the stations use the same learning algorithm and - due to the broadcast nature of the network - the feedback information is common for all of them. Furthermore, all the stations use the same random number generator and the same seed. Therefore, at each time slot, all the stations arrive at the same decision on which station grants permission to transmit [9]. Thus, the protocol is collision-free.

Since the offered traffic is bursty, when the selected station has a packet to transmit, it is probable that this station will have packets to transmit in the near future. Therefore, when the selected station transmits a packet, then the automaton is fed with a reward. On the other hand, when the selected station has no packet to transmit, it is probable that this station will remain idle in the near future. In this case, the automaton is fed with a penalty. According to this scheme, stations which had packets transmissions in the near past are selected more frequently than other stations. Furthermore, due to the use of a stochastic estimator, stations that have not been selected recently, have the opportunity to be selected. Therefore, the SE-TDMA protocol is capable of being adapted to the sharp changes of the dynamic bursty traffic environment.

The set of actions is defined as: $A = \{a_1, \ldots, a_N\}$, where N is the number of stations. At each time slot t, the learning automaton randomly selects an action $a(t)$ according to the probability distribution $P(t) = \{p_1(t), \ldots, p_N(t)\}$. If $a(t) = a_i$, then station u_i grants permission to transmit during time slot t. The result of this decision (packet transmission or idle slot) is used as feedback information in the following way:

i) $b(t) = 1$ (reward) if the selected station u_i transmitted a packet during time slot t.

ii) $b(t) = 0$ (penalty) if slot t was idle, since the selected station u_i had no packets to transmit.

Theorem: If d_i is the reward probability of action a_i, for $i = 1, \ldots, N$ and $R(t) = \sum_{i=1}^{N} d_i \, p_i(t)$, then $E[R(t+1)|P(t)] > R(t)$ for all t and all $p_i(t) \in (0,1)$ $(i = 1, \ldots, N)$.

Proof: The proof is given in [16]. Although, an S-model environment is considered in [16], the proof is also valid for a P-model environment, since the stochastic estimates $g_i(t)$ are continuous random variables symmetrically distributed about their means d_i (for $i = 1, \ldots, N$).

$R(t)$ represents the probability that slot t is not idle. Since at each time slot, $R(t)$ is increased, it follows that the number of idle slots asymptotically tends to be minimized. Therefore, the throughput of a network operating under the SE-TDMA protocol tends to be maximized.

4 Simulation Results

In the following, the proposed SE-TDMA protocol is compared to TDMA [2]-[8] and RTDMA [9],[10]; two representative time division multiple access protocols.

The protocols which are under comparison were simulated to be applied to three different networks (N_1, N_2 and N_3) under bursty traffic conditions. The bursty traffic was modelled in a way similar to the ones presented in [17] and [18]. Each node can be in one of two states S_0 and S_1. When a node is in state S_0 then it has no packet arrivals. When a node is in state S_1 then at each time slot it has a packet arrival with probability Z. Given a station is in state S_0 at time slot t, the probability that this station will transit to state S_1 at the next time slot is P_{01}. The transition probability from state S_1 to state S_0 is P_{10}. It can be shown that, when the load offered to the network is R packets/slot and the mean burst length is B slots, then the transition probabilities are: $P_{10} = 1/B$ and $P_{01} = \frac{R}{B(NZ-R)}$.

The number of users N, the queue size Q, the mean burst length B and the packet arrival probability Z of each active station, were taken to be as follows:

a) Network $N_1 : N = 10, Q = 10, B = 10, Z = 1.0$

b) Network $N_2 : N = 20, Q = 15, B = 10, Z = 1.0$

c) Network $N_3 : N = 5, Q = 3, B = 1000, Z = 0.8$

We have used the following two broadly used performance metrics in order to compare the three protocols:

1) The delay versus throughput characteristic.

2) The throughput versus offered load characteristic.

The delay versus throughput characteristics of the compared protocols when they are applied to networks N_1, N_2 and N_3 are appeared at figures 1, 3 and 5, correspondingly.

The throughput versus offered load characteristics of the compared protocols when they are applied to networks N_1, N_2 and N_3 are appeared at figures 2, 4 and 6, correspondingly. In the simulation of protocol SE-TDMA, we have used the optimal values of the internal parameters of SELA (a, W, n, σ_{max}) for each one of the above networks.

From the comparative graphs, it becomes clear that, SE-TDMA achieves a significantly higher delay-throughput and throughput-load performance than protocols TDMA and RTDMA, when operating under bursty traffic conditions. The performance improvement which is achieved by the use of SE-TDMA is higher when the offered traffic is more bursty (i.e. when the mean burst length is high).

5 Conclusion

This paper has presented a new time division multiple access protocol for broadcast networks. According the proposed SE-TDMA protocol, the station which grants permission to transmit at each time slot is selected by means of learning automata, which are capable of being adapted to the changes of the stations' traffic. Therefore, the new protocol is capable of achieving a low delay and a high throughput in the dynamic bursty traffic environment.

The main characteristics of the SE-TDMA protocol are summarized below:

a) It achieves a high performance, even when the offered traffic is bursty.

b) It is self-adaptive. Thus, when the traffic conditions change, the choice probabilities of the stations are rapidly adapted to the new traffic conditions.

c) No centralized control of the stations is required, since the protocol is fully distributed.

d) It is fault-tolerant, since its operation is not affected from a possible node failure.

e) No significant increase of the implementation cost is introduced. The only additional hardware - in relation to

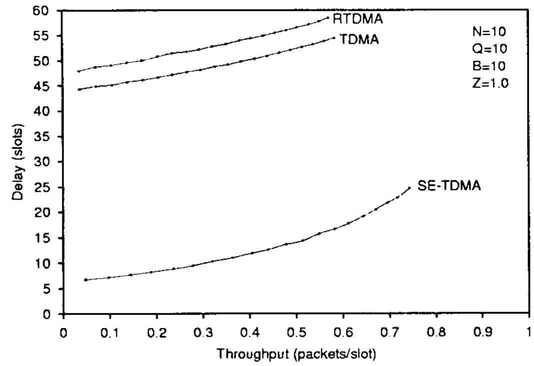

Figure 1: The Delay versus Throughput characteristics of SE-TDMA, TDMA and RTDMA when applied to network N_1.

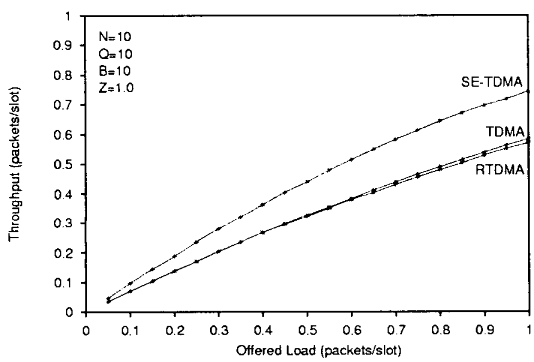

Figure 2: The Throughput versus Load characteristics of SE-TDMA, TDMA and RTDMA when applied to network N_1.

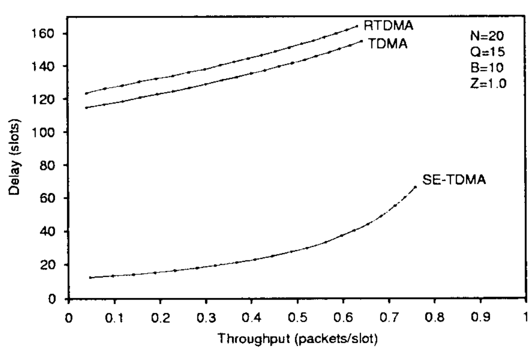

Figure 3: The Delay versus Throughput characteristics of SE-TDMA, TDMA and RTDMA when applied to network N_2.

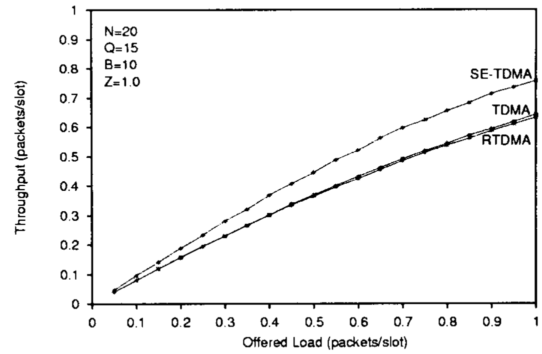

Figure 4: The Throughput versus Load characteristics of SE-TDMA, TDMA and RTDMA when applied to network N_2.

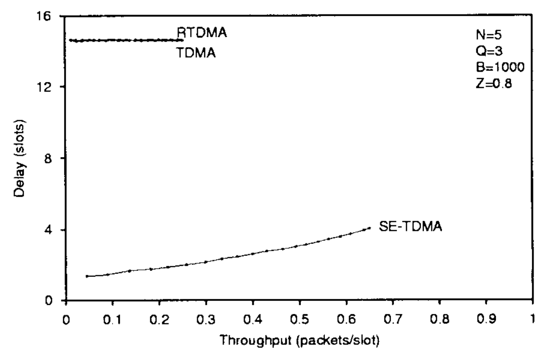

Figure 5: The Delay versus Throughput characteristics of SE-TDMA, TDMA and RTDMA when applied to network N_3.

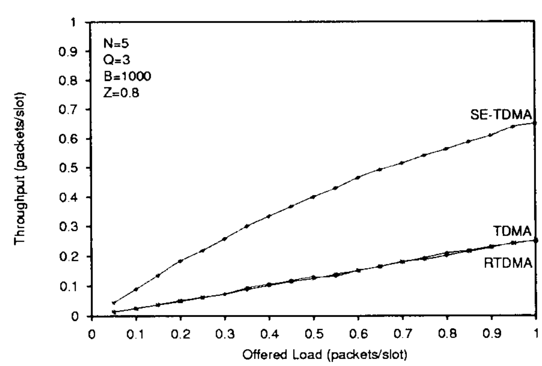

Figure 6: The Throughput versus Load characteristics of SE-TDMA, TDMA and RTDMA when applied to network N_3.

TDMA or RTDMA - is a processor which implements the learning algorithm.

The use of learning automata offers a new highly promising approach to the design of self-adaptive multiaccess protocols for broadcast networks. We are currently working on this direction.

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