Learning Automata - Based Random Access Protocols for WDM Passive Star Networks

GEORGIOS I. PAPADIMITRIOU and DIMITRIS G. MARITSAS

Department of Computer Engineering, University of Patras, Patras, Greece.

ABSTRACT: A Learning Automata - Based Random Access (LABRA) protocol for WDM Passive Star Networks is introduced. The proposed protocol makes use of learning automata in order to achieve a high throughput and a low delay under any load conditions. An array of learning automata which determines the transmission probability of each wavelength is placed at each station. After each time slot the transmission probability of each wavelength is modified according to the network feedback information. The asymptotic behavior of the system which consists of the automata and the network is analyzed and it is proved that under any load conditions, the transmission probability asymptotically tends to take its optimum value. Furthermore, extensive simulation results are presented, which indicate that the use of the proposed learning automata-based scheme leads to a significant improvement of the network's performance.

I. INTRODUCTION

A WDM Passive Star network using tunable lasers and fixed optical filters, which operates under the slotted ALOHA protocol [2],[3], is considered in this paper. The key issue in such a network is the determination of the transmission probability p, with which each ready station transmits at the beginning of each time slot. Since the optimum value of p depends on the network's load, a fixed choice of p leads to a significant decrease of the network's performance when the latter operates under variable load conditions.

In this paper, a new random access protocol which makes use of learning automata [6]-[7] in order to dynamically determine the transmission probability p is introduced. The structure of this paper is as follows: Section II introduces the reader to the use of the slotted ALOHA protocol in WDM passive star networks. The presentation of the proposed LABRA protocol in Section III is followed by an analysis of the asymptotic behavior of the system which consists of the automata and the network in Section IV. Simulation results which indicate that a significant performance improvement is achieved when the LABRA protocol is used in a WDM Passive Star network, are presented in Section V. Finally, some remarks concerning a possible extension of the LABRA protocol close the paper in Section VI.

II. PASSIVE STAR NETWORKS USING THE SLOTTED ALOHA PROTOCOL

The network under consideration is a WDM Passive Star network using the architectural form which is presented in [2] and [3] (fig.1).

Each transmitter is provided with a tunable laser which can be tuned at each one of the W available wavelengths. Optical fibers are used in order to connect the output of each laser to one of the input ports of a N×N (where N is the number of stations) star coupler at the network hub. Thus, at each output port of the coupler, all the wavelengths are available. Each output port of the star coupler is connected to the corresponding receiver, by means of an optical fiber. At each receiver the optical signal is fed to a fixed optical filter which passes only one wavelength.

A protocol commonly used in a network of the above architectural form is the slotted ALOHA. According to this protocol, when a station has a packet to transmit, then it tunes its laser at the receiver's wavelength and transmits the packet with transmission probability p. If two or more stations concurrently transmit on the same wavelength, then all the transmitted packets are destroyed. Such a situation is called "collision". Each colliding station, senses the collision [4] and retransmits the collided packet at the next time slot, with probability p.

Assume that at a time instant t, M stations are waiting to transmit on a specific wavelength, say λ_i. The probability that a successful transmission will take place at this wavelength is: $P_{suc}(t) = M\,p\,(1-p)^{M-1}$. It is known that the right hand side of the above relation is maximized when $p=1/M$. Thus, for users waiting to transmit on wavelength λ_i, the optimum value of the transmission probability depends on the total number of these users, which in turn, depends on the offered load. When the network operates under variable load conditions and the transmission

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probability p is fixed, then the throughput of the network is decreased, since the protocol is not capable of being adapted to the load changes.

In this paper, a new self-adaptive protocol which dynamically determines the transmission probability p, is introduced. Due to its adaptivity, the proposed protocol is capable of operating efficiently under any load conditions.

III. THE LABRA PROTOCOL

The optimum transmission probability differs from wavelength to wavelength and depends on the number of packets waiting to be transmitted at each wavelength. According to the LABRA protocol, each station uses an array of learning automata in order to determine the transmission probability of each wavelength. The LABRA protocol and its hardware implementation (fig.2) are described below:

III.1. The determination of the transmission probability

The set of stations is defined as $U=\{u_1,u_2,\ldots,u_N\}$ where N is the number of stations. The set of wavelengths is defined as $\Lambda=\{\lambda_1,\lambda_2,\ldots,\lambda_W\}$ where W is the number of wavelengths.

An array of W learning automata $LA_1,LA_2,\ldots,LA_W$ is placed at each station u_k. Each automaton LA_i corresponds to a specific wavelength λ_i and at any time instant contains the "transmission probability" $P_i(t)$ of the λ_i wavelength. At each time slot t, each station u_k which is ready to transmit on wavelength λ_i, transmits the packet with probability $P_i(t)$. The transmission is postponed with probability $1-P_i(t)$. If the transmission is postponed or the transmitted packet is destroyed due to a collision, then the same operation is repeated at the next time slot.

III.2. The feedback mechanism

Each station is provided with a WDM demultiplexer which separates the different wavelengths. Each one of the separated wavelengths is detected for collision. The collision detection operation can be implemented either by computing the checksum of the packet's header or by measuring the optical power of the signal by means of a photoFET. At each time slot, the collision detection information of each wavelength λ_i, is fed to the wavelength-specific learning automaton LA_i which updates the transmission probability $P_i(t)$, by means of a learning algorithm. Since, the feedback is common for all the stations, it follows that the corresponding automata of all the stations always contain the same transmission probabilities.

The role of the WDM demultiplexer is double. Except of providing the automata with feedback information, it also replaces the fixed optical filter. If station u_k passes only the λ_i wavelength, it is only needed to connect the corresponding output of the WDM demultiplexer to the receiving buffer (fig.2).

In this study, the end-to-end propagation delay is assumed to be negligible. Therefore, the network feedback information is immediately available for use. Some remarks concerning the application of the LABRA protocol to networks with large end-to-end propagation delay are given in Section VI.

III.3. The probability updating scheme

The key issue of the proposed protocol is the determination of the transmission probabilities $P_i(t)$ for $i=1,2,\ldots,W$. A high transmission probability $P_i(t)$ would lead to a large number of collisions at wavelength λ_i. On the other hand, a relatively small $P_i(t)$ would lead to a large number of idle slots at wavelength λ_i. In both cases, the throughput of wavelength λ_i is decreased. The throughput of wavelength λ_i is maximized when the transmission probability takes an optimum value which depends on the number of users waiting to transmit on this wavelength.

If M users are ready to transmit on wavelength λ_i at time slot t, then the probability that a successful transmission will take place at the λ_i wavelength is:

$$P_{suc}(t) = M\, P_i(t)\, (\, 1-P_i(t)\,)^{M-1} \quad (1)$$

The probability that wavelength λ_i will be idle during the time slot t is:

$$P_{id}(t) = (\, 1-P_i(t)\,)^{M} \quad (2)$$

Since the success probability $P_{suc}(t)$ is maximized when $P_i(t)=1/M$, we must choose $P_i(t)=1/M$ in order to maximize the throughput of wavelength λ_i. However, the value of M is unknown. Therefore, there is a serious problem on how to determine the optimum value of $P_i(t)$.

According to the LABRA protocol, a learning automaton is used in order to determine the transmission probability of each wavelength. The occurrence of an idle slot is probably due to a small value of the transmission probability $P_i(t)$. Thus, $P_i(t)$ must be increased. A successful transmission implies that the number of packets waiting for transmission at the λ_i wavelength is probably decreased. Therefore, the transmission probability $P_i(t)$ must be increased. Due to the above reasons, if the λ_i wavelength was idle or a successful transmission took place during the last time slot, then the LA_i automaton increases the transmission probability $P_i(t)$.

On the other hand, the occurrence of a collision during the last time slot is probably due to a high value of the transmission probability. Therefore, the LA_i automaton decreases the transmission probability $P_i(t)$ when a collision occurs at wavelength λ_i.

Assume that $S_i(t) \in$ { IDLE, SUCCESS, COLLISION } denotes the state of wavelength λ_i during the time slot t. The general probability updating scheme which must be used by the automata of the LABRA protocol is the following:

$P_i(t+1)=P_i(t)+\Delta_1$ if $S_i(t)$=IDLE or SUCCESS

$P_i(t+1)=P_i(t)-\Delta_2$ if $S_i(t)$=COLLISION

where: $0<\Delta_1<1-P_i(t)$ and $0<\Delta_2<P_i(t)$ (3)

Our aim is to appropriately choose Δ_1 and Δ_2, so that the transmission probability $P_i(t)$ asymptotically tends to be equal to 1/M. The design of such an updating scheme is possible, and it is based on the following two remarks:

Remark A: When $P_i(t)=1/M$, then the reward probability $d_i(t)=P_{suc}(t)+P_{id}(t)$ is approximately equal to $2e^{-1}$. From relations (1) and (2) it is derived that if $P_i(t)=1/M$ then $\lim_{M\to\infty} d_i(t) = 2e^{-1} = 0.736$. Furthermore, for small values of M (M≥2), the reward probability $d_i(t)$ takes values very close to $2e^{-1}$. (Relations (1) and (2) give: $M=2 \Rightarrow d_i(t)=0.750$, $M=3 \Rightarrow d_i(t)=0.741$, $M=4 \Rightarrow d_i(t)=0.738$, $M=5 \Rightarrow d_i(t)=0.737$, etc).

Remark B: For any wavelength λ_i (with M≥2), the reward probability $d_i(t)$ is a monotonically decreasing function of the transmission probability $P_i(t)$.

Proof: It suffices to show that the first derivative of the function $D_i(P_i) = (1-P_i)^M + M P_i (1-P_i)^{M-1}$ is negative for $P_i \in (0,1)$ and M≥2. We have: $D_i'(P_i)=-M(M-1)P_i(1-P_i)^{M-2}<0$.

Remark A guarantees that the - unknown - optimum value of $P_i(t)$ ($P_i(t)=1/M$) corresponds to a known value of $d_i(t) = 2e^{-1} = 0.736 = v$, irrespective of the value of M.

Remark B implies that the wanted value of $d_i(t)= v$ can be achieved by increasing or decreasing the value of $P_i(t)$. By analyzing the general updating scheme (3) we have:

$$E[\delta P_i(t)] = E[P_i(t+1) - P_i(t)] =$$
$$= d_i(t)\,\Delta_1 - (1-d_i(t))\,\Delta_2 =$$
$$= (\Delta_1+\Delta_2)\,(d_i(t) - \Delta_2/(\Delta_1+\Delta_2)) \quad (4)$$

In order to asymptotically converge to the point $d_i(t)=v$, the probability updating scheme, must satisfy the following three properties (where $\delta d_i(t)=d_i(t+1)-d_i(t)$): i) if $d_i(t)>v$ then $E[\delta P_i(t)] >0$ and consequently, $E[\delta d_i(t)]<0$. ii) if $d_i(t)<v$ then $E[\delta P_i(t)] <0$ and consequently, $E[\delta d_i(t)] >0$. iii) if $d_i(t)=v$ then $E[\delta P_i(t)]=0$ and consequently, $E[\delta d_i(t)] = 0$.

Relation (4) guarantees that all the above properties are satisfied when: $\Delta_2/(\Delta_1+\Delta_2)=v$ or equivalently: $\Delta_1=((1-v)/v)\Delta_2 = h\,\Delta_2$ with $h=(1-v)/v = (1-2e^{-1})/2e^{-1} = 0.359$.

If we set $\Delta_2 = \Delta$, then the general probability updating scheme becomes:

$$P_i(t+1)=P_i(t) + h\,\Delta \quad \text{if } S_i(t)=\text{IDLE or SUCCESS}$$
$$P_i(t+1)=P_i(t) - \Delta \quad \text{if } S_i(t)=\text{COLLISION}$$
where: $0<\Delta<(1-P_i(t))/h$ and $0<\Delta<P_i(t)$.

It remains to choose the appropriate value of Δ. We selected $\Delta=L\ P_i(t)(1-P_i(t))$ with $0<L<1$. This choice of Δ leads to the following updating scheme:
$$P_i(t+1) = P_i(t) + h\ L\ P_i(t)\ (1-P_i(t))$$
if $S_i(t)$=IDLE or SUCCESS
$$P_i(t+1) = P_i(t) - L\ P_i(t)\ (1-P_i(t))$$
if $S_i(t)$=COLLISION

where: $L \in (0,1)$.

However, the above scheme has a serious disadvantage. When the transmission probability $P_i(t)$ takes values in the neighborhood of 0 or 1, then the probability updating step becomes very small. This leads to a serious loss of the automaton's adaptivity and consequently, to a serious decrease of the network's performance. In order to eliminate this disadvantage, the probability updating scheme is modified in the following way:
$$P_i(t+1) = P_i(t) + h\ L\ P_i(t)\ (1-P_i(t)) + a\ L^2\ (1-P_i(t))^2 \quad \text{if } S_i(t)=\text{IDLE or SUCCESS}$$
$$P_i(t+1) = P_i(t) - L\ P_i(t)\ (1-P_i(t)) - b\ L^2\ (P_i(t))^2 \quad \text{if } S_i(t)=\text{COLLISION}$$
where: $L \in (0,1)$ and $a,b \in (0,\ 1/L)$.

IV. PERFORMANCE ANALYSIS

The asymptotic behavior of the above probability updating scheme is analyzed and it is proved that for small values of the L parameter, the transmission probability $P_i(t)$ asymptotically tends to take its optimum value. The above proposition is formally expressed as follows:

Theorem 1: Assume that the following probability updating scheme is used:
$$P_i(t+1) = P_i(t) + h\ L\ P_i(t)\ (1-P_i(t)) + a\ L^2\ (1-P_i(t))^2 \quad \text{if } SLOT_i(t)=\text{IDLE or SUCCESS}$$
$$P_i(t+1) = P_i(t) - L\ P_i(t)\ (1-P_i(t)) - b\ L^2\ (P_i(t))^2 \quad \text{if } SLOT_i(t)=\text{COLLISION}$$
where: $L \in (0,1)$ and $a,b \in (0,\ 1/L)$.
If M packets are waiting to be transmitted at the λ_i wavelength, then: $\lim_{\substack{L\to 0\\ t\to\infty}} P_i(t) = 1/M$.

Note: The number M of packets which are waiting to be transmitted on a specific wavelength, say λ_i, is slowly varying with the time. However, theorem 1 guarantees that the LABRA protocol always tends to satisfy the condition $P_i(t)=1/M$.

Proof: As it was mentioned in Section III the function $D_i(P_i)$ which expresses the reward probability as a function of the transmission probability P_i is defined as follows:
$$D_i(P_i) = (1-P_i)^M + M\ P_i\ (1-P_i)^{M-1}$$
There exists a P_i^* with $0<P_i^*<1$ such that:
$D_i(P_i^*)=v$ and $(P_i-P_i^*)(D_i(P_i)-v)<0$ for all $P_i \neq P_i^*$

Note: Remark A of Section III ensures that $P_i^* \simeq 1/M$. Now, lets define $\delta P_i(t)=P_i(t+1)-P_i(t)$. If $d_i(t)=D_i(P_i(t))$ we have:
$$E[\delta P_i(t)\,|\ P_i(t)] =$$
$$= L\ (1+h)\ P_i(t)\ (1-P_i(t))\ (d_i(t) - v) +$$
$$+ L^2\ (a\ d_i(t)(1-P_i(t))^2 - b(1-d_i(t))(P_i(t))^2)$$

To prove Theorem 1 we shall use the following theorem which is presented in [7].

Let $\{x(t)\}_{t\geq 0}$ be a stationary Markov Process dependent on a constant parameter $\theta\in[0,1]$. Each $x(t)\in I$ where I is a subset of the real line. Let $\delta x(t) = x(t+1)-x(t)$.
The following are assumed to hold:
1) I is compact.
2) $E[\delta x(t)\,|\,x(t)=y] = \theta\ \omega(y) + O(\theta^2)$
3) $E[\,|\delta x(t)|^2\ |x(t)=y] = \theta^2\ b(y) + O(\theta^2)$
4) $E[\,|\delta x(t)|^3\ |x(t)=y] = O(\theta^3)$

where:
$\sup_{y\in I}\frac{O(\theta^k)}{\theta^k}<\infty$ for $k=2,3$ and $\sup_{y\in I}\frac{O(\theta^2)}{\theta^2}\to 0$ as $\theta\to 0$.
5) $\omega(y)$ has a Lipschitz derivative in I.
6) $b(y)$ is Lipschitz in I.

The following theorem concerns the behavior of $\{x(t)\}$ for small values of θ.

Theorem B: If assumptions 1) to 6) hold, $\omega(y)$ has a unique root y^* in I and $d\omega/dy\,|_{y=y^*}<0$ then: a) $\mathrm{var}[x(t)\,|\,x(0)=x]=O(\theta)$ uniformly for all $x\in I$ and $t\geq 0$. b) For any $x\in I$ the differential equation $\frac{dy(\tau)}{d\tau}=\omega(y(\tau))$ has a unique solution $y(\tau)=y(\tau,x)$ with $y(0)=x$ and $E[x(t)\,|\,x(0)=x] = y(t\theta)+O(\theta)$ uniformly for all $x\in I$ and $t\geq 0$. c) $(x(t)-y(t\theta))/\sqrt{\theta}$ has a normal distribution with zero mean and finite variance as $\theta\to 0$ and $t\theta\to\infty$.

In order to apply the above theorem to the proof of Theorem 1 we have to identify $x(t)$ with $P_i(t)$, θ with L and I with (0,1). If $d_i = D_i(P_i)$, we have:

$$E[\delta P_i(t) \mid P_i(t)=P_i] = L\ \omega(P_i)$$

$$E[\,|\delta P_i(t)|^2 \ \mid P_i(t)=P_i\,] = L^2\ b(P_i) + O(L^2)$$

$$E[\,|\delta P_i(t)|^3 \ \mid P_i(t)=P_i\,] = O(L^3)$$

where $\omega(P_i)$ and $b(P_i)$ are the following:

$$\omega(P_i) = (1+h)\ P_i\ (1-P_i)\ (d_i-v) + \\ + L\ (\ a\ d_i\ (1-P_i)^2 - b\ (1-d_i)\ (P_i)^2\ )$$

$$b(P_i) = (\ P_i\ (1-P_i)\ )^2\ (1 + d_i(h^2-1)\ )$$

It is immediately seen that assumptions 1) to 4) are satisfied. It can also be proved that $b(P_i)$ and $\omega'(P_i)$ are Lipschitz in (0,1) by showing that their first derivatives are bounded [8] for $P_i \in (0,1)$. It remains to show that $\omega(P_i)$ has a unique root P_i^r near the point P_i^* (which is defined by the relation $D_i(P_i^*)=v$) and that: $d\omega(P_i)/dP_i\,|_{P_i=P_i^r} < 0$.

Since, $\omega(0) = L\ a > 0$, $\omega(1) = -L\ b < 0$ and $\omega(P_i)$ is a continuous function it follows that $\omega(P_i)$ has at least one root P_i^r in the unit interval. Since,

$$\omega(P_i) = (1+h)\ P_i\ (1-P_i)\ (d_i-v) + \\ + L\ (\ a\ d_i\ (1-P_i)^2 - b\ (1-d_i)\ (P_i)^2\ )$$

and L can be arbitrarily small, there are only three probable roots of $\omega(P_i)$ in the (0,1) interval. i) one root in the neighborhood of the point $P_i=0$. ii) a second root in the neighborhood of the point $P_i=1$. iii) a third root in the neighborhood of the point $P_i=P_i^*$. The relation $\omega(P_i^r)=0$ can be written as follows (where $d_i^r = D_i(P_i^r)$):

$$(1+h)\ P_i^r\ (1-P_i^r)\ (d_i^r-v) = \\ = -L\ (a\ d_i^r\ (1-P_i^r)^2 - b\ (1-d_i^r)\ (P_i^r)^2) \qquad (5)$$

If we assume that $\omega(P_i)$ has a root P_i^r in the neighborhood of 0 or in the neighborhood of 1, then relation (5) is an absurdity, since the left hand side and the right hand side of the above relation have different signs. Therefore, $\omega(P_i)$ has not a root in the neighborhood of 0 or in the neighborhood of 1. Consequently, $\omega(P_i)$ has a unique root P_i^r in the unit interval. This root is in the neighborhood of P_i^*. Note, that P_i^r can be as close to P_i^* as desired, by selecting a small enough parameter L. Now, if we define $d_i^r = D_i(P_i^r)$ and $d_i^{r\prime} = D_i'(P_i^r)$ we have:

$$d\omega(P_i)/dP_i\,|_{P_i=P_i^r} = \\ = (1+h)\ \left[(d_i^r-v)\ (1-2P_i^r) + P_i^r\ (1-P_i^r)\ d_i^{r\prime}\right] + \\ + L\ \left[\ a\ d_i^{r\prime}\ (1-P_i^r)^2 - 2\ a\ (1-P_i^r)\ d_i^r + \\ + b\ d_i^{r\prime}\ (P_i^r)^2 - 2\ b\ (1-d_i^r)\ P_i^r\ \right] < \\ < (1+h)\ \left[(d_i^r-v)\ (1-2P_i^r) + P_i^r\ (1-P_i^r)\ d_i^{r\prime}\right] \qquad (6)$$

From the proof of Remark B it is known that $d_i^{r\prime} < 0$. Consequently, $P_i^r\ (1-P_i^r)\ d_i^{r\prime} < 0$. If we select a small enough parameter L, the quantity (d_i^r-v) can be as close to 0 as desired. Consequently, we can select a small enough parameter L so that:

$$(d_i^r-v)\ (1-2P_i^r) + P_i^r\ (1-P_i^r)\ d_i^{r\prime} < 0$$

In this case, relation (6) becomes:

$$d\omega(P_i)/dP_i\,|_{P_i=P_i^r} < 0 \qquad \text{q.e.d.}$$

It has been shown that $\omega(P_i)$ has a unique root P_i^r in the neighborhood of P_i^* with $d\omega(P_i)/dP_i\,|_{P_i=P_i^r} < 0$. If we set $P_i(\tau) = P_i^r$, the differential equation $dP_i(\tau)/d\tau = \omega(P_i(\tau))$ is satisfied (0=0). Thus, $P_i(\tau)=P_i^r$ is a solution of the above differential equation. From Theorem B, it is derived that this solution is unique, thus, all the solutions starting in (0,1) of the differential equation $\frac{dP_i(\tau)}{d\tau} = \omega(P_i(\tau))$ converge to the point $P_i(\tau) = P_i^r \simeq P_i^* \simeq 1/M$. According to Theorem B, we have: $\lim_{t\to\infty} E[P_i(t)] = P_i^* + O(L)$ and $var[P_i(t)] = O(L)$ for all t. Consequently, $\lim_{\substack{L\to 0\\ t\to\infty}} P_i(t) = 1/M$ q.e.d.

V. SIMULATION RESULTS

In the following, the proposed LABRA protocol is compared to the well-known slotted ALOHA protocol, which is presented in [2] and [3]. This protocol was chosen for the following two reasons:

1) Both protocols are applied to WDM Passive Star networks using tunable lasers and fixed receivers.

2) The LABRA protocol can be considered as an extension of the slotted ALOHA protocol. Therefore, a performance comparison between the two protocols will clearly demonstrate the performance improvement which is due to the use of the new learning automata-based scheme.

The two protocols which are under comparison were simulated to be applied to two different networks (N_1 and N_2). The number of stations N and the number of wavelengths W of each simulated network, were taken to be as follows: Network N_1: N=8, W=4. Network N_2: N=24, W=8. For both networks, the total bandwidth was taken to be equal to 10 Gbps. The packet size was equal to 1000 bits, while the queue size was 3 packets. The fixed receiver of each station u_i passes only the λ_j wavelength, with $j=\lceil i/W \rceil$. All the stations have the same arrival rate of packets, with packet arrivals following the Poisson model.

The internal parameters of the automata used by the LABRA protocol were taken to be: L=0.3, a=0.1 and b=3.0. For each simulated network, the slotted ALOHA protocol was simulated for three different values of the fixed transmission probability P_i. In any case, the values of P_i were appropriately selected, so that it is guaranteed that there is not any other value of P_i which leads to a considerably higher throughput of the slotted ALOHA protocol. For each one of the two simulated networks, the fixed values of P_i were chosen as follows. N_1: P_i=0.25, 0.30 and 0.35. N_2: P_i= 0.10, 0.15 and 0.20.

We have used the following two broadly used performance metrics in order to compare the LABRA protocol with the slotted ALOHA one: 1) The delay versus throughput characteristic. 2) The throughput versus offered load characteristic. The delay versus throughput characteristics of the LABRA and the slotted ALOHA protocols when they are applied to the networks N_1 and N_2 are appeared at figures 3 and 5, correspondingly. The throughput versus offered load characteristics of the two compared protocols when they are applied to the networks N_1 and N_2 are appeared at figures 4 and 6, correspondingly.

From the above graphs, it becomes clear that under any load conditions, the LABRA protocol achieves a higher throughput and a lower delay than the slotted ALOHA one.

VI. CONCLUSION

In this paper we have presented a learning automata-based random access protocol, which achieves a high performance under any load conditions. In this study, the end-to-end propagation delay was assumed to be negligible. However, the LABRA protocol can be applied to networks with large end-to-end propagation delay, by making use of pipelining [5].

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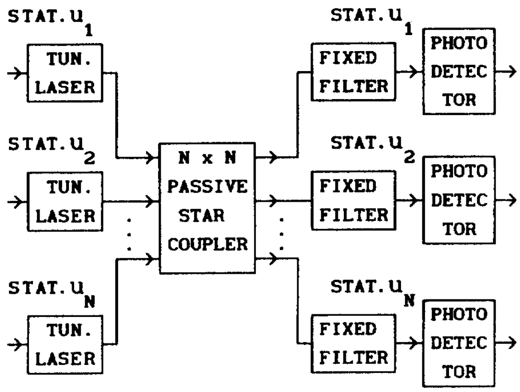

Fig. 1: A WDM Passive Star Network.

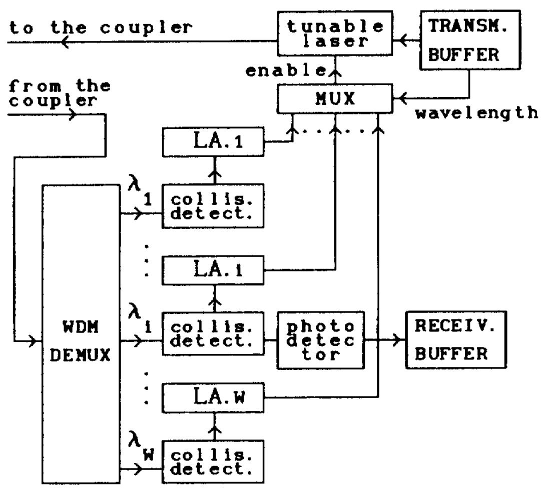

Fig. 2: A station of a LABRA network.

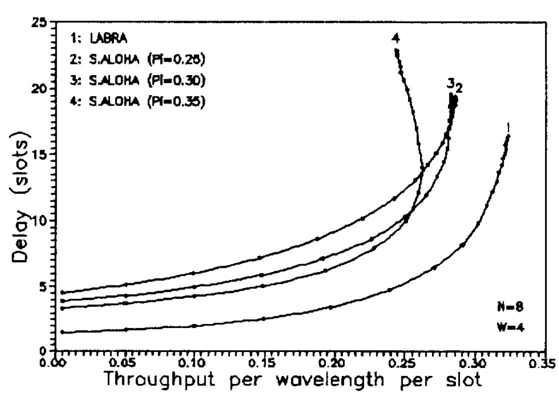

Fig. 3: Net. N_1 - Delay vs Throughput.

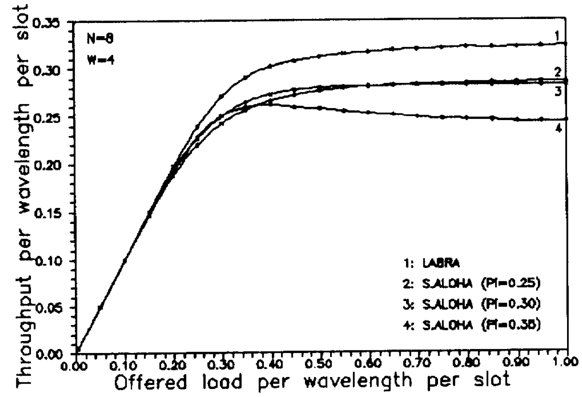

Fig. 4: Net. N_1 - Throughput vs Load.

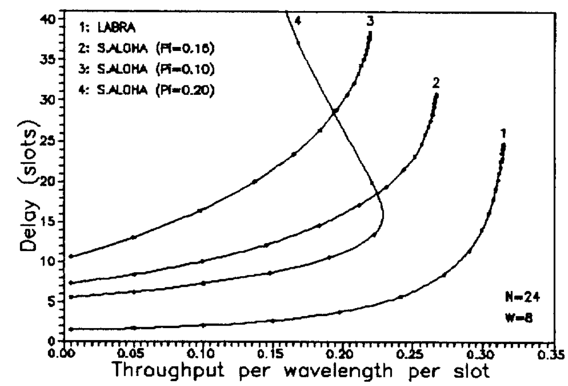

Fig. 5: Net. N_2 - Delay vs Throughput.

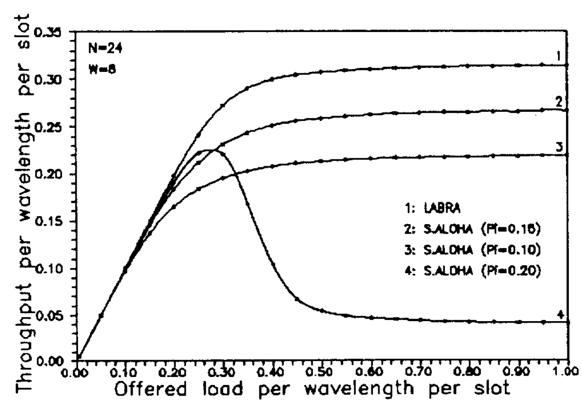

Fig. 6: Net. N_2 - Throughput vs Load.