LABON: A LEARNING AUTOMATA-BASED OPTICAL NETWORK

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ABSTRACT: A WDM Optical Network which makes use of learning automata in order to achieve a high throughput and a low delay under any load conditions is introduced. An array of learning automata which control the passing of the transmitted packets to the Star Coupler is placed at the network hub. Each wavelength is controlled by a specific automaton which contains the probability that a packet transmitted at this wavelength will pass to the star coupler. After each time slot the passing 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 passing probability asymptotically tends to take its optimum value. Furthermore, simulation results are presented, which indicate that a significant performance improvement is achieved when the proposed learning automata - based passing mechanism is used.

I. INTRODUCTION

The increasing bandwidth demands of the emerging new generation of LANs and MANs have led to the use of optical fiber as a transmission medium. Due to the limited speed of the stations' electronic circuits, single channel optical networks - such as FDDI, DQDB, etc - were not proved capable of supporting Gigabit data rates. The introduction of the Wavelength Division Multiplexing (WDM) technique [1],[2] solved this problem by dividing the available optical bandwidth into multiple channels of lower bandwidth which can be easily supported by the stations' electronic circuits. Passive Star networks are WDM networks which use a Passive Star Coupler in order to broadcast all inputs to all outputs. A Passive Star network using tunable lasers and fixed optical filters (fig.1) which operates under the slotted ALOHA protocol [4],[5], 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 network architecture which makes use of learning automata [9] in order to dynamically determine the transmission probability p is introduced. 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 architecture leads to a significant improvement of the network's performance.

The structure of this paper is as follows. Section II introduces the reader to the WDM Passive Star architectural form which is considered in this paper. The presentation of the proposed LABON architecture in Section III is followed by the description of the proposed learning protocol in Section IV. The analysis of the asymptotic behavior of the system which consists of the automata and the network is presented in Section V. Simulation results which indicate that a significant performance improvement is achieved when the LABON architecture is used in a WDM Passive Star network, are presented in Section VI. Finally, some remarks concerning the possible extensions of the LABON architecture close the paper in Section VII.

II. THE WDM PASSIVE STAR ARCHITECTURAL FORM

One of the most commonly used architectural forms of WDM Passive Star networks is the one using tunable lasers and fixed optical filters [2],[4],[5],[6] (fig.1). Each transmitter is provided with a tunable laser which can be tuned at each one of the W available wavelengths, while each receiver is provided with a fixed optical filter which passes only one wavelength. A protocol commonly used in networks of the above architectural form, is the slotted ALOHA protocol [4],[5]. 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

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transmission probability p. If two or more stations concurrently transmit at the same wavelength, then all the transmitted packets are destroyed. In such a situation which is called "collision", all the collided packets are retransmitted at the next time slot with probability p.

Assume that at a time instant t, M stations are waiting to transmit at 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 at the λ_i wavelength, 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 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.

Unfortunately, the network usually operates under variable load conditions, due to the following two reasons:

i) Traffic in Gigabit LANs is highly bursty. Data traffic, which constitutes most of load is intrinsically bursty. As the network speed increases, the peak rate increases faster than the average, thus making traffic becoming even more bursty.

ii) Even if the load offered to a WDM Passive Star network using the ALOHA protocol is stable, the load of each specific wavelength is time variable. Assume that instantly, a large number of packets are trying to be transmitted at a specific wavelength, say λ_i. This wavelength suffers from a large number of collisions, which decreases its throughput. Therefore, the transmission rate probably becomes lower than the arrival rate, at the λ_i wavelength. Consequently, the number of packets waiting for transmission at the λ_i wavelength further increases, causing a vicious circle. This situation which is termed as "wavelength overloading" leads to a dramatic decrease of the network's throughput.

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

III. THE LABON ARCHITECTURE

The optimum transmission probability differs from wavelength to wavelength and depends on the number of packets waiting to be transmitted at each wavelength. The proposed Learning Automata - Based Optical Network (LABON) makes use of learning automata [9] in order to determine the transmission probability p of each wavelength. When a station has a packet to transmit, then the packet is transmitted with probability one. An array of learning automata which control the passing of the transmitted packets to the Star Coupler is placed at the network hub. Each wavelength is controlled by a specific automaton which contains the probability that a packet transmitted at this wavelength will pass to the Star Coupler. Since, each packet is transmitted with probability one and its passing to the Star Coupler is probabilistically decided at the network hub, the term "transmission probability" must be replaced by the term "passing probability". After each time slot the passing probability of each wavelength is modified according to a network feedback information.

The LABON network can be divided into three basic modules which are described below. The reader can consult figure 2 in order to study an example of the LABON architecture for three stations and two wavelengths.

III.1 The Broadcast-and-Select Module

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

Each transmitter is provided with a tunable laser which can be tuned at all the W available wavelengths. Optical fibers are used to connect the output of the lasers to the network hub. There, each optical signal passes via an acoustooptic tunable filter (AOTF) which has multiple wavelength selection capability [8]. At any time slot t, each filter F_k (k=1,...,N) is tuned to pass only a subset of wavelengths $\Lambda_k(t)$ (with $\Lambda_k(t) \subseteq \Lambda$).

Assume that a user u_k transmits at the λ_i wavelength at time slot t. If $\lambda_i \in \Lambda_k(t)$ then the signal passes to the star coupler. Otherwise, the signal is cut by the acoustooptic filter F_k. The outputs of the acoustooptic filters are connected to the input ports of the Star Coupler. The output ports of the Star Coupler are connected to the receivers via optical fibers. Each receiver is provided with a fixed optical filter which passes only one wavelength.

III.2 The Control Module

An array of W two-action learning automata $LA_1,...,LA_W$ which control the passing of the transmitted packets to the Star Coupler is placed at the network hub. Each wavelength λ_i is controlled by a specific automaton which contains the probability $P_i(t)$ that a packet transmitted at this wavelength will pass to the star coupler. At the beginning of each time slot, each automaton LA_i $(i=1,...,W)$ chooses N random numbers $r_{1,i}(t),...,r_{N,i}(t)$ uniformly distributed in the range of (0,1). If $r_{k,i}(t) < P_i(t)$ $(k=1,...,N)$ then the filter F_k allows the wavelength λ_i to pass to the star coupler. Thus, $\lambda_i \in \Lambda_k(t)$. Otherwise, if $r_{k,i}(t) \geq P_i(t)$ then the filter F_k cuts the λ_i wavelength. Thus, $\lambda_i \notin \Lambda_k(t)$.

III.3 The Feedback Module

At the end of each time slot, each learning automaton updates the passing probability according to the state of the corresponding wavelength during the last time slot. The automata are informed of the state of the channel during the last time slot in the following way. One of the output ports of the star coupler is connected to a WDM demultiplexer which separates the different wavelengths. Each wavelength is detected for collision and the feedback information for each wavelength is fed to the corresponding automaton. The collision detection operation is implemented by computing the checksum of the packet's header. After being informed of the state of the channel, the automaton updates the passing probability according to a learning algorithm which will be described in the next section.

IV. THE LEARNING PROTOCOL

When a station (let u_k) has a packet to transmit, it tunes its laser at the receiver's wavelength (let λ_i) and transmits the packet with probability one. The filter F_k will pass the signal with probability $P_i(t)$. Consequently, each packet which is transmitted at the λ_i wavelength, will pass to the star coupler with probability $P_i(t)$.

The transmitter can ascertain the result of its transmission by using one of the methods reported in [3]. If the packet will not reach its destination (because it was collided with another packet or it was cut by the F_k filter) then, it is retransmitted at the next time slot.

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

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

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

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

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

As it was discussed earlier, the success probability $P_{suc}(t)$ is maximized when $P_i(t)=1/M$. Consequently, we must choose $P_i(t)=1/M$ in order to maximize the throughput of the λ_i wavelength. 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 LABON architecture, a learning automaton is used in order to determine the passing probability of each wavelength. The occurrence of an idle slot is probably due to a small value of the passing probability $P_i(t)$. Therefore, $P_i(t)$ 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 passing 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 passing 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 passing probability. Therefore, the LA_i automaton decreases the passing probability $P_i(t)$ when a collision occurs at the λ_i wavelength.

Assume that $SLOT_i(t) \in \{$ Idle, Success, Collision $\}$ denotes the state of the λ_i wavelength during the t time slot. The general probability updating scheme which must be used by the automata of the LABON architecture is the following:

$P_i(t+1)=P_i(t)+\Delta_1$ if $SLOT_i(t)$=Idle or Success

$P_i(t+1)=P_i(t)-\Delta_2$ if $SLOT_i(t)$=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 passing 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: $M=2 \Rightarrow d_i(t)=0.750$, $M=3 \Rightarrow d_i(t)=0.741$, $M=4 \Rightarrow d_i(t)=0.738$, etc).

REMARK B: For any wavelength λ_i (with M≥2), the reward probability $d_i(t)$ is a monotonically decreasing function of the passing 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: $\Delta_1 = \frac{1-v}{v} \Delta_2 = h\ \Delta_2$ with $h = \frac{1-v}{v} = \frac{1-2e^{-1}}{2e^{-1}} = 0.359$.

If we set $\Delta_2 = \Delta$, then the general updating scheme (3) becomes:

$P_i(t+1)=P_i(t)+h\ \Delta$ if $SLOT_i(t)$=Idle or Success

$P_i(t+1)=P_i(t)-\Delta$ if $SLOT_i(t)$=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 $SLOT_i(t)$=Idle or Success

$$P_i(t+1) = P_i(t) - L\ P_i(t)\ (1-P_i(t))$$
if $SLOT_i(t)$=Collision

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

However, the above scheme has a serious disadvantage. When the passing 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:

$$P_i(t+1) = P_i(t) + h\ L\ P_i(t)\ (1-P_i(t)) + a\ L^2\ (1-P_i(t))^2 \quad \text{if } SLOT_i(t)=\text{Idle or Success}$$

$$P_i(t+1) = P_i(t) - L\ P_i(t)\ (1-P_i(t)) - L^2\ (P_i(t))^2 \quad \text{if } SLOT_i(t)=\text{Collision}$$

where: $L \in (0,1)$ and $a,b \in (0,\ 1/L)$.

V. 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 passing 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:

$$P_i(t+1) = P_i(t) + h\ L\ P_i(t)\ (1-P_i(t)) + a\ L^2\ (1-P_i(t))^2 \quad \text{if } SLOT_i(t)=\text{Idle or Success}$$

$$P_i(t+1) = P_i(t) - L\ P_i(t)\ (1-P_i(t)) - L^2\ (P_i(t))^2 \quad \text{if } SLOT_i(t)=\text{Collision}$$

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: $\lim_{\substack{L\to 0 \\ t\to\infty}} P_i(t) = 1/M$

Proof: For the sake of brevity the proof is omitted. It can be found in [6].

VI. SIMULATION RESULTS

In the following, the proposed LABON network is compared to a WDM passive star network using the well-known slotted ALOHA protocol, which is presented in [5]. This architecture - which in the rest of this paper is simply called slotted ALOHA architecture - was chosen for the following two reasons:

1) It uses the same variant of the Passive Star configuration with the LABON architecture. Thus, is uses tunable lasers and fixed optical filters.

2) The LABON architecture can be separated into two parts. The basic slotted ALOHA architecture and the Learning Automata mechanism which is placed at the network hub. Therefore, a performance comparison between the two architectures will clearly demonstrate the performance improvement which is due to the use of the new learning automata - based architecture.

The two architectures which are under comparison were simulated to be applied in two different networks: N_1 and N_2. The number of nodes N and the number of wavelengths W of each simulated network, were taken to be as follows: N_1: N=12, W=4. N_2: N=16, 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 optical filter of each node u_i passes only the λ_j wavelength, with $j=\lceil i/W \rceil$. Each node is assumed to have only packet switched traffic. All the nodes have the same arrival rate of packets, with packet arrivals following the Poisson model.

The internal parameters of the automata used by the LABON architecture were taken to be: L=0.3, a=0.1 and b=3.0. These values of the parameters of the automata were selected because they give satisfactory results in all the simulated networks.

For each simulated network, the slotted ALOHA architecture 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 ensured that there is not any other value of P_i which leads to a considerably higher throughput of the slotted ALOHA protocol. For the two simulated networks, the fixed values of P_i were chosen as follows: P_i=0.15, 0.20 and 0.25.

We have used the following two broadly used performance metrics in order to compare the LABON architecture 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 LABON and the slotted ALOHA architectures 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 architectures 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 LABON architecture achieves a higher throughput and a lower delay than the slotted ALOHA one. One might expect that for some values of load - for example, when the average number of ready stations per wavelength is equal to $1/P_i$ - the slotted ALOHA architecture would achieve a higher throughput than the LABON one. However, even when the total load offered to the network is fixed, the load offered at each specific wavelength is time variant, due to the "wavelength overloading" which was described in Section II. Therefore, the throughput of the LABON architecture, remains higher than the one of the slotted ALOHA, under any load conditions. This applies to both high and low load conditions, either the load is variable or fixed.

VII. CONCLUSION

In this paper we have presented a learning automata-based optical network, which achieves a high performance under any load conditions. An analysis of the asymptotic behavior of the LABON network proves that the passing probability of each wavelength, asymptotically tends to take its optimum value. Furthermore, simulation results indicate that a significant performance improvement is achieved when the proposed learning automata-based architecture is used.

The LABON architecture can be modified in one of the following two ways:

1) In this paper, the end-to-end propagation delay was assumed to be negligible. However, the LABON architecture is also applicable in networks with large end-to-end propagation delay, without any modification of its performance. This extension of the LABON architecture is based on the use of pipelining. A detailed description of the pipelined LABON architecture is beyond the scope of this paper.

2) The LABON architecture can also be implemented in a distributed manner, by placing a separate array of automata at each station. The reader can consult [6] in order to study this approach.

VIII. REFERENCES

[1] I.Chlamtac and W.R.Franta,"Rationale, Directions and Issues Surrounding High Speed Networks", Proceedings of the IEEE, vol.78, no.1, pp.121-132, January 1990.

[2] C.A.Brackett, "Dense Wavelength Division Multiplexing Network: Principles and Applications", IEEE Journal on Selected Areas in Communications, vol.8, no.6, pp.948-964, August 1990.

[3] K.M.Sivalingam, K.Bogineni and P.W.Dowd, "Pre-Allocation Media Access Control Protocols for Multiple Access WDM Photonic Networks", SIGCOMM'92, August 17-20, 1992, Baltimore, Maryland, U.S.A.

[4] A. Ganz, "End-to-End Protocols for WDM Star Networks", IFIP/WG6.1-WG6.4 Workshop on Protocols for High-Speed Networks, Zurich, Switzerland, May 1989.

[5] A.Ganz and Z.Koren, "WDM Passive Star - Protocols and Performance Analysis", IEEE INFOCOM'91, 7-11 April 1991, Bal Harbour, Florida, U.S.A.

[6] G.I.Papadimitriou and D.G.Maritsas, "Learning Automata - Based Random Access Protocols for WDM Passive Star Networks", IEEE GLOBECOM'93, November 29 - December 2, 1993, Houston, Texas, U.S.A.

[7] G.I.Papadimitriou and D.G.Maritsas, "WDM Passive Star Networks: Receiver Collision Avoidance Algorithms using Multifeedback Learning Automata", IEEE 17th Conference on Local Computer Networks, 13-16 September 1992, Minneapolis, Minnesota, U.S.A.

[8] K.W.Cheung, "Acoustooptic Tunable Filters in Narrowband WDM Networks: System Issues and Network Applications", IEEE Journal on Selected Areas in Communications, vol.8, no.6, pp.1015-1025, August 1990.

[9] K.S.Narendra and M.A.L.Thathachar, "Learning Automata: An Introduction", Prentice Hall, Englewood Cliffs, New Jersey, 1989.

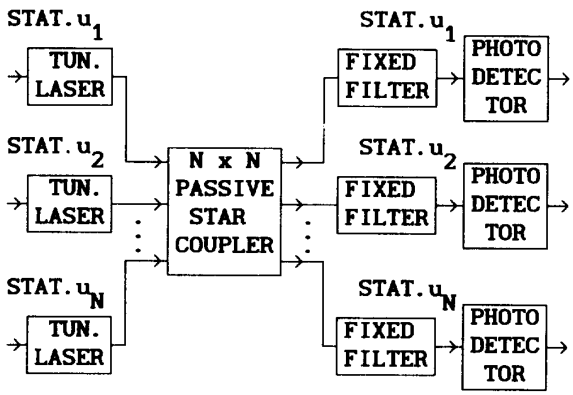

Fig. 1: A WDM Passive Star Network.

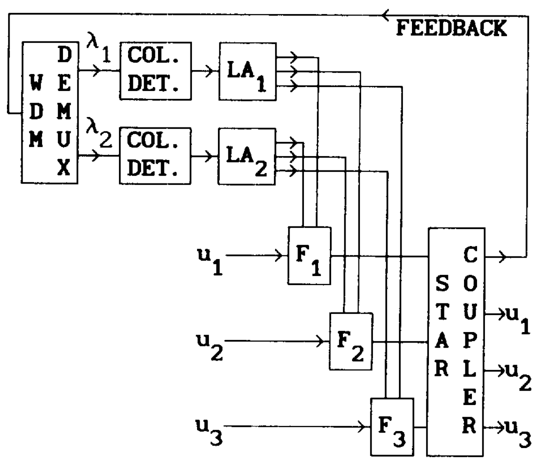

Fig. 2: The network hub of LABON.

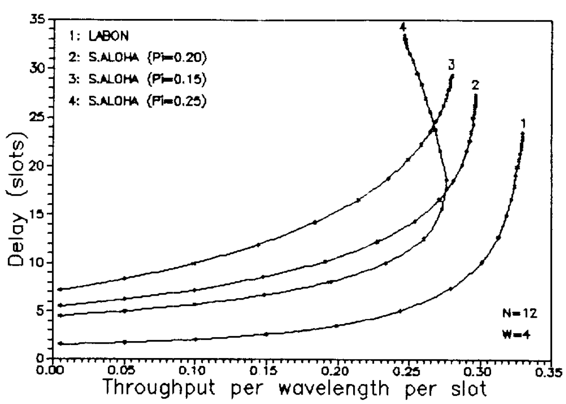

Fig. 3: Net. N_1 - Delay vs Throughput.

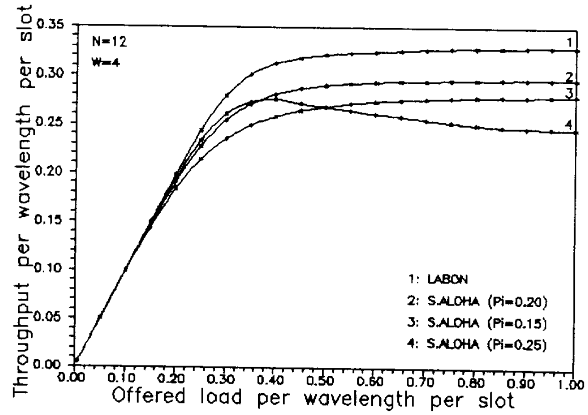

Fig. 4: Net. N_1 - Throughput vs Load.

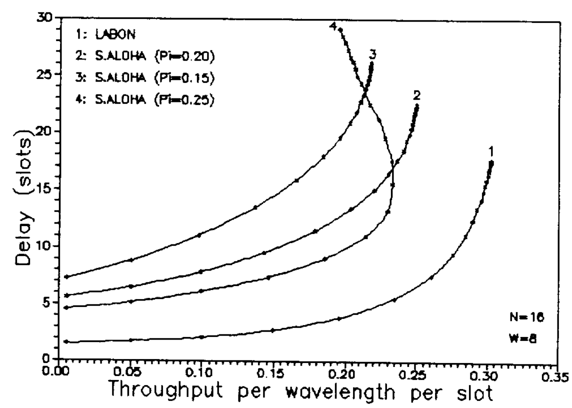

Fig. 5: Net. N_2 - Delay vs Throughput.

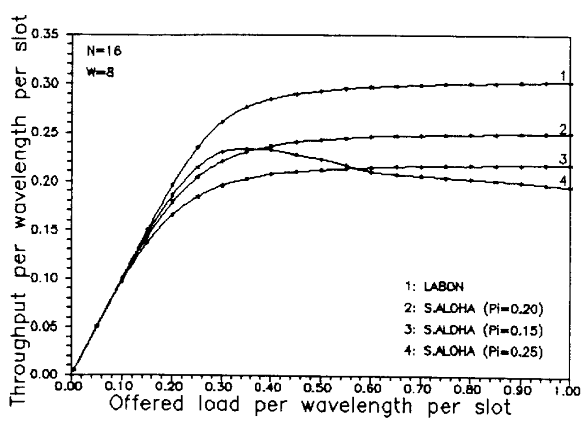

Fig. 6: Net. N_2 - Throughput vs Load.