Transient Analysis of Photonic Networks

Kriti Priya Gupta[1] Madhu Jain[2]
1.Symbiosis Centre for management Studies (SCMS), NOIDA,Symbiosis International University (SIU), Pune, India
2.Department of Mathematics,Indian Institute of Technology Roorkee, India

Abstract
The behavior of slotted aloha protocol for a star-coupled Wavelength Division Multiple Access (WDMA) photonic network is studied. Semi-markov process is used for developing the steady state and transient models for the protocol. The performance of the network is evaluated in terms of various measures viz. average number of packets in the network, throughput of the network and average packet delay etc. The analytical models are validated by evaluating the numerical values of the performance indices, which are further compared by using Adaptive Neuro Fuzzy Inference System (ANFIS) approach.
Keywords: Photonic networks, Slotted aloha, Semi-markov process, Neuro-fuzzy systems, Throughput.

1. Introduction

The advancement of light wave technology over the past decade has revolutionized long distance communications. Research on photonics switching has been motivated due to the advantages of fiber optical in high-speed networks, distributed networks, Broadband Integrated Service Digital Networks (BISDN) etc. Highly motivated by the impressive results of fiber optic technology in the eighties and nineties, various scenarios predicted a telecommunication infrastructure based on all-optical networks including optical frequency division multiplexing (OFDM), information super-highways, coherent receivers with tunable lasers, all-photonics switching networks and finally fiber-to-the-home (FTTH) with ATM-based digital broadband accesses. The introduction of high-quality, interactive multimedia services like video-on-demand (VoD) require high bit rate accesses and system upgradation to much larger capacities. The continuously increasing demand of higher transmission capacity has resulted in the enhancement of photonic (optical) networks.

The photonic networks are generally built by using passive star couplers. Dowd [1989, 1990] discussed star-coupled parallel interconnection in optical networks. In the star topology, each station is connected to a central node or a hub through point-to-point links. The hub, which can be an active or a passive device, directs the flow of traffic to all other stations. In case of a passive hub, the star topology becomes a broadcasting system, in which, the incoming signals are equally shared among all the stations. Star coupled networks have high fault tolerance due to their passive nature and complete connectivity. Pre-allocation techniques are usually employed as the media access control protocols for wavelength division multiple access (WDMA) star-coupled photonic networks. The pre-allocation techniques eliminate the requirement that a node possess both a tunable transmitter and a tunable receiver. This reduces the implementational and operational complexities of the network.

Wavelength division multiplexing (WDM) is an emerging technology for increasing the bandwidth of optical networks (Ugale and Mishra, 2011; Mishra et. al., 2011). The advent of real-time multimedia services over the Internet has stimulated new technologies for achieving the high level of Quality of Service (QoS) guarantee for sensitive multimedia traffic and for expanding the capacity of optical network backbones (Amphawan and Abraham, 2002; Amphawan et al., 2010; Stepniak et al, 2011; Amphawan, 2011). Various routing algorithms for reducing packet delays and alleviating network congestions for multimedia traffic have been developed (Li and Dimyati, 2009; Pevac et al., 2011; Deepalakshmi, 2012).

The performance modelling and analysis of the photonic networks has attracted the attention of many researchers. Mehravari [1990] analyzed the performance of very high-speed optical fiber local area networks using a passive star topology. Ganz and Koren [1991] examined the performance of WDM passive star-protocols. Sivalingam et. al. [1992] studied the behavior of static and random access protocols for multiple access WDM photonic networks. The protocols considered by them were based on an architecture with one tunable transmitter and one fixed receiver at each node. But, they assumed that the transmitter could only have one packet in the buffer. Huanga and Ma (2009) presented a performance model for differentiated service over single-hop passive star coupled WDM optical networks.

In this investigation, we analyze the behavior of slotted aloha protocol for a star-coupled WDMA photonic network. We consider that the transmitter has a finite buffer in which, more than one packet can wait for the service. Transient as well as steady state models are developed for the protocol by employing a Semi-markov process. Analytical expressions are obtained for various performance measures of the network viz. average number of packets in the network, throughput of the network and average packet delay etc.

We also approximate the performance measures by using neuro fuzzy systems (NFS). Neuro-fuzzy systems are employed to facilitate the soft computing approaches, which combine artificial neural networks (ANNs) and fuzzy systems (FS). Biologically, these systems resemble the nervous systems, where the ANNs are analogous to the neural cells which are low-level perceptive, responsible for the signal integration while the FS are equivalent to the brain which provides high level reasoning and linguistic abilities. In this study, we use a special class of neuro-fuzzy systems, i.e. Adaptive Network-based Fuzzy Inference Systems (ANFIS) that can identify parameters by using supervised learning methods. The ANFIS learning algorithm is a hybrid supervised method based on gradient descent and least square methods. A survey on fusion technology of fuzzy technology and neural networks is done by Takagi [1990]. Jang and Sun [1993] studied the learning algorithms of adaptive network-based fuzzy inference systems. More detailed descriptions of adaptive neuro fuzzy systems can be found in Cornelius and Leondes [1998] and Tettamanzi and Tomassini [2001]. Neuro-fuzzy technique is an emerging soft-computing methodology which has been successfully applied in telecommunication systems for call admission control, parameter estimation, routing, traffic policing, ATM traffic shaping and flow control, network management etc. Nelson and Tham [2000] employed an integrated neural network and fuzzy controller to implement a call admission controller. They exploited the learning ability of the neural network and the robustness of the fuzzy controller.

The rest of the paper is organized as follows: In section 2, we describe the architecture of ANFIS employed for the prediction of neuro-fuzzy results. The analytical traffic model of the photonic network is developed in section 3. The queue size distributions for both transient and steady state models are also provided. Various performance measures of the network are discussed in section 4. In section 5, the performance measures are established by using neuro-fuzzy approach. Numerical illustrations for comparing the analytical results with the neuro-fuzzy results are provided in section 6. Finally the conclusions are drawn in the last section 7.

2. Adaptive Network-based Fuzzy Inference Systems (ANFIS)

ANFIS is a network representation of Tagaki-Sugeno-Kang (TSK) type fuzzy systems with learning capabilities. TSK is a special type of fuzzy rule-based system in which rules are of the form

IF x_1 is A_1 AND x_2 is A_2…AND x_n is A_n THEN $y=f(x_1,x_2,\dots,x_n)$

where f is usually a linear combination of the input variables i.e.

$f(x_1,x_2,\dots,x_n)=w_0+w_1x_1+\dots+w_nx_n$

Here w_0, $w_1,\dots,w_n$ are real constants which are part of the rule specification. The combined result of applying the rules of a TSK system is a crisp number, which is computed as the average of the outputs of the single rules weighted by the degrees of truth of their antecedents. This is a particular case of the weighted average method of defuzzification.

The ANFIS heterogeneous architecture constitutes a number of layers where each layer has a number of nodes. For example, a fuzzy inference system with one input x and one output y can be described by the following n rules using TSK model:

IF x is A_1 THEN $f_1=p_1x+r_1$
IF x is A_2 THEN $f_2=p_2x+r_2$
…
…
…
IF x is A_n THEN $f_n=p_nx+r_n$

The corresponding ANFIS network architecture is depicted in fig. 1. As can be seen from the figure, there are many layers in the network. Let $O_{l,i}$ be the output of node *i* in layer *l*. The functionalities of all the layers are as follows:

Layer 1: Each node in the 1st layer is an adaptive unit with output

$$O_{1,i}=\mu_{A_i}(x)=w_i, \qquad i=1,2,\dots,n$$

where x is the input value and A_i's are the associated fuzzy sets. Here w_i is the firing strength of each node. The membership functions for each A_i can be any function among triangular, trapezoidal, gaussian or bell-shaped.

Layer 2: Each node in this layer calculates the ratio of the ith rule's firing strength to the sum of all the rules' firing strengths, i.e.

$$O_{2,i}=\overline{w}_i=\frac{w_i}{\sum_{i=1}^{n}w_i}, \qquad i=1,2,\dots,n$$

Layer 3: Each node in this layer has the following function:

$$O_{3,i}=\overline{w}_i f_i=\overline{w}_i(p_i x+r_i), \qquad i=1,2,\dots,n$$

Layer 4: The single node in this layer aggregates the overall output as the summation of all the incoming signals, i.e.

$$O_{4,1} = \sum_{i=1}^{n} \overline{w}_i f_i = \frac{\sum_{i=1}^{n} w_i f_i}{\sum_{i=1}^{n} w_i}$$

3. Analytical Traffic Model

We consider a photonic network with M nodes, which are interconnected by C channels. Each node in the network is assumed to have a tunable transmitter and a fixed receiver. The transmission of the packets in the network occurs according to the slotted aloha protocol where a source node transmits on the home channel of the destination node as soon as a packet is generated (cf. Sudhakar et. al. [1991]). A packet slot is divided into two sub-slots: transmission sub-slot and acknowledgement sub-slot. During the transmission sub-slot, the source node transmits a packet to the destination node while in the acknowledgement sub-slot, the destination node transmits an acknowledgement to the source node. In case the source node doesn't receive any acknowledgement, then it implies that a collision has occurred and the packet hasn't reached the destination. In such situation, the transmitter of the source node backs off from transmitting, and retransmits the packet with a backoff probability P_b. We employ a semi-markov model for analyzing the network. Following are the assumptions and notations being used in the formulation of the traffic model:

Assumptions:

- The packets at each node are generated according to Poisson distribution.
- All packets in the network are of fixed length.
- At each node, at most one new packet can arrive at a time.
- All the nodes have finite transmitter buffers in which S packets can be buffered at most.
- All nodes are identical and independent.
- In the beginning, when no packet is generated in the network, the transmitter is in idle state and as soon as a packet is generated, the transmitter enters the transmission state.

Notations:

S	Buffer size of the transmitter
I	The state representing that the transmitter is idle
T_i	The state representing that the transmitter is transmitting a packet with i packets in the buffer (i=0,1,…,S)
B_i	The state representing that the transmitter is in backoff state with i packets in the buffer (i=0,1,…,S)
$P_s(t)$	Transient probability that a packet is transmitted successfully
P_s	Steady state probability that a packet is transmitted successfully
$P_j(t)$	Transient state probability representing that the transmitter is in state j (j=I, T_0, T_1,…,T_S, B_0, B_1,…,B_S)
P_j	Steady state probability representing that the transmitter is in state j (j=I, T_0, T_1,…,T_S, B_0, B_1,…,B_S)
	Packet generation rate per node when the transmitter is in idle state
(=1-e^{-})	Probability that one packet is generated in a slot when the transmitter is in idle state
	Packet generation rate per node when the transmitter is not in idle state
(=1-e^{-})	Probability that one packet is generated in a slot when the transmitter is not in idle state

The probability of successful transmission P_s,(t) is given by (cf, Sivalingam et. al. [1992])

$$P_s(t) = (1 - P_{transmit}(t)/C)^{(M-1)} \qquad \ldots(1)$$

where $P_{transmit}(t)$ is the probability that the transmitter is in transmitting state.

A semi-markov model is employed for analyzing the slotted aloha protocol for the considered photonic network. We focus on the behavior of a single node of the network. Fig. 2 depicts the state diagram of the process of one node. Now, we construct Chapman Kolomogorov equations (cf. Klienrock, 1975) governing the model as follows:

$$\frac{dP_I(t)}{dt} = -\beta P_I(t) + (1-\beta) P_S(t) P_{T_0}(t) \qquad (2.1)$$

$$\frac{dP_{T_0}(t)}{dt} = -[(1-\beta)P_s(t)+\beta(1-P_s(t))+(1-P_s(t))(1-\beta)]P_{T_0}(t)+P_b(1-\beta)P_{B_0}(t) + P_s(t)P_{T_1}(t)+\beta P_I(t) \tag{2.2}$$

$$\frac{dP_{T_i}(t)}{dt} = -[P_s(t)+\beta(1-P_s(t))+(1-P_s(t))(1-\beta)]P_{T_i}(t)+P_b(1-\beta)P_{B_i}(t) + P_s(t)P_{T_{i+1}}(t)+\beta P_b P_{B_{i-1}}(t) \qquad ,i=1,2,\ldots,S-1 \tag{2.3}$$

$$\frac{dP_{T_S}(t)}{dt} = -[P_s(t)+(1-P_s(t))]P_{T_S}(t)+P_bP_{B_S}(t)+\beta P_bP_{B_{S-1}}(t) \qquad \ldots(2.4)$$

$$\frac{dP_{B_0}(t)}{dt} = -[P_b(1-\beta)+\beta P_b+\beta(1-P_s(t))]P_{B_0}(t)+(1-P_s(t))(1-\beta)P_{T_0}(t) \qquad \ldots(2.5)$$

$$\frac{dP_{B_i}(t)}{dt} = -[P_b(1-\beta)+\beta P_b+\beta(1-P_s(t))]P_{B_i}(t)+\beta(1-P_s(t))P_{B_{i-1}}(t) +(1-P_s(t))(1-\beta)P_{T_i}(t)+\beta(1-P_s(t))P_{T_{i-1}}(t) \qquad ,i=1,2,\ldots,S-1 \tag{2.6}$$

$$\frac{dP_{B_S}(t)}{dt} = -P_bP_{B_S}(t)+\beta(1-P_s(t))P_{B_{S-1}}(t)+(1-P_s(t))P_{T_S}(t)+\beta(1-P_s(t))P_{T_{S-1}}(t) \tag{2.7}$$

Following are steady state equations obtained from eqns. (2)-(14):

$$P_I = (1-\beta)P_I + (1-\beta)P_sP_{T_0} \qquad \ldots(3.1)$$

$$P_{T_0} = \beta P_I + \beta P_sP_{T_0} + P_sP_{T_1} + P_b(1-\beta)P_{B_0} \qquad \ldots(3.2)$$

$$P_{T_i} = P_sP_{T_{i+1}} + \beta P_bP_{B_{i-1}} + P_b(1-\beta)P_{B_i} \qquad ,i=1,2,\ldots,S-1 \qquad \ldots(3.3)$$

$$P_{T_S} = \beta P_bP_{B_{S-1}} + P_bP_{B_S} \qquad \ldots(3.4)$$

$$P_{B_0} = (1-P_s)(1-\beta)P_{T_0} + (1-P_b)(1-\beta)P_{B_0} \qquad \ldots(3.5)$$

$$P_{B_i} = \beta(1-P_s)P_{T_{i-1}} + (1-P_s)(1-\beta)P_{T_i} + \beta(1-P_s)P_{B_{i-1}} + (1-P_b)(1-\beta)P_{B_i} \qquad ,i=1,2,\ldots,S-1 \qquad \ldots(3.6)$$

$$P_{B_S} = \beta(1-P_s)P_{T_{S-1}} + (1-P_s)P_{T_S} + \beta(1-P_s)P_{B_{S-1}} + (1-P_b)P_{B_S} \qquad \ldots(3.7)$$

Queue size distribution:

The transient and steady state queue size distributions can be obtained by solving the set of equations (2) and (3) respectively. There are many iterative methods for solving the set of differential equations like SOR (successive over-relaxation) method, Newton Raphson method etc. But we employ Runge-Kutta method of fourth order for solving the transient equations. For the steady state equations, we use the "fsolve" routine of MTLAB package for obtaining the numerical values of steady state probabilities. This routine uses the Gauss-Newton method for solving the set of algebraic equations.

4. Performance Analysis

After obtaining the queue size distributions, we obtain some performance measures for the photonic network using the above-determined probabilities as follows:

- **Transmission state probability:**
  The probability that the transmitter is in transmitting state can be obtained by,

$$P_{transmit}(t) = \sum_{i=0}^{S} P_{T_i}(t) \quad \text{...(4)}$$

- **Backoff state probability:**
  This is the probability, which represents that the transmitter is in the backoff state and can be expressed as

$$P_{backoff}(t) = \sum_{i=0}^{S} P_{B_i}(t) \quad \text{...(5)}$$

- **Average number of packets in the network:**
  The average number of packets in the network is given by

$$E(N)(t) = E_I P_I(t) + \sum_{i=0}^{S} E_i P_{T_i}(t) + \sum_{i=0}^{S} E_i P_{B_i}(t) \quad \text{...(6)}$$

  where E_I=0, E_0=1, E_1=2, E_2=3, E_3=4, E_4=5,...,E_S=S-1

- **Throughput:**
  It is defined as the total number of packets successfully transmitted per slot across all the channels. For a particular node, the number of packets transmitted successfully is determined by the probability that the transmitter is in transmitting state and the probability of successful transmission. Hence, the total network throughput TP is obtained as

$$TP(t) = M \cdot P_{transmit}(t) P_s(t) \quad \text{...(7)}$$

- **Average packet delay:**
  The packet delay is the time gap between the packet generation at the source node and the packet receipt at the destination node. Mathematically, average pcket delay at a single node can be obtained by using Little's law as

$$D = \frac{E(N)}{\gamma} \ ,$$

where is the throughput per node. Hence,

$$D(t) = \frac{M \cdot E(N)(t)}{TP(t)} \quad \text{...(8)}$$

The performance measures for the steady state model can be determined in a similar manner by using the steady state probabilities obtained form eq. (3)

5. Neuro-Fuzzy Model

In this section, we discuss the neuro-fuzzy approach for computing various performance measures of the photonic network described in the previous section. The ANFIS network for approximating the average number of packets E(N), network throughput TP and the average packet delay D for the steady state and transient models are built by using the fuzzy toolbox of the MATLAB package. The performance measures are obtained by varying various parameters like packet generation rate λ, time period T, number of nodes M and number of channels C. These parameters are treated as the linguistic variables in the context of the fuzzy systems. While building the respective ANFIS networks, these parameters are taken as the input values. The gaussian function is used for describing the membership functions for the various input parameters. Table 1 provides the number of functions and the corresponding linguistic values of the input parameters and the shapes of the corresponding membership functions are shown in fig.3.

Table 1: Linguistic values of the membership functions for various input parameters

Input variable	No. of membership functions	Linguistic values
Packet generation rate ( )	5	• Very low • Low • Average • High • Very high
Time period (T)	5	• Shortest • Shorter • Short • Medium • Lengthy
No. of nodes (M)	2	• Less • Large
No. of channels (C)	2	• Less • Large

6. Numerical Illustrations

The analytical results for steady state and transient semi-markov models obtained in the previous sections are validated through numerical experiments. The steady state probabilities are computed numerically by Gauss-Newton method, using the 'fsolve' routine of MATLAB. For the transient model, the Runge-Kutta method (RKM) of fourth order is used for solving the system of differential equations, which is implemented by exploiting MATLAB's 'ode45' function. A time span of [0-100] is taken with equal intervals of 10 units. The numerical results obtained for various performance indices of both steady state and transient models are also compared with neuro-fuzzy results by building ANFIS networks in MATLAB 6.0. For all the approximations, the ANFIS networks are trained for 10 epochs. For illustration purpose, we take the buffer size of the transmitter as S=5.

Figures 4-6 plot the numerical results for the steady state model by taking the backoff probability P_b=0.05. The graphs in figures 4(a-b), 5(a-b) and 6(a-b) depict respectively the average number of packets in the system E(N), network throughput TP and average packet delay D by varying the packet generation rate for various values of M and C. The continuous lines depict the case where the packet generation rates in the idle state and the transmission and backoff states are homogeneous i.e., $\lambda_0=\lambda$ whereas the broken lines illustrate the case of heterogeneous packet generation rates i.e., $\lambda_0=.9\lambda$ It can be seen that the values of all the performance indices are lesser for homogeneous rates than that for the heterogeneous rates. From figures 4 and 5, we note that as more number of packets are generated in the network, the average number of packets and the throughput of the network increase rapidly. On the other hand, fig. 6 shows that average packet delay initially increases and then becomes almost constant for higher packet generation rates. This implies that packet delay can be controlled in the network to a certain extent for higher loads. Also, D increases with M and decreases with C. Hence if the number of channels is increased in proportion to the number of nodes, then the performance of the network in terms of packet delay can be maintained up to a certain level. Further, it can be seen from fig. 5(b) that the throughput increases with C. The increase in the number of channels decreases the number of collisions of the packets. Therefore it results in a better throughput and less delay of packets.

In figs. 7 and 8, the numerical results using "fsolve" and the results using ANFIS are exhibited for throughput and delay. We observe that ANFIS results are quite closer to the numerical results in all the cases. Here, we also notice that TP increases with the increase in λ, M and C. The average packet delay D increases rapidly for low arrival rates but for higher arrival rates, D shows very slight increase. With the increase in the system size, i.e. the number of nodes in the network, M, the delay increases rapidly which is quite obvious. However, D can be decreased by increasing the number of channels C.

In figs. 9, 10 and 11, the curves for E(N), D and TP respectively are plotted with respect to time T for the transient model. The continuous lines show the RKM results and the broken lines depict the ANFIS results. It is clear that all the performance measures become steady after a particular time. Further, for shorter time periods, E(N) and D increase with the increase in T. Also TP shows a rapid decrease with T. This implies that as time passes, the performance of the network degrades but this degradation becomes constant after a particular time as all the performance measures becomes almost constant for large values of T.

In table 2, the steady state transmission and backoff state probabilities of the transmitter are displayed by varying λ for various values of C and M. We note that if the packet generation rate is high, then for the case when C=32 and M=16, the transmission state probabilities are greater and the backoff state probabilities are

lesser than for the cases when C=32, M=32 or C=16, M=32. Therefore, if more channels are provided in comparison to the number of nodes in the network, then the number of collisions can be reduced which results in lesser retransmissions of the packets and hence an improved network performance.
Overall, we conclude that

- The network performance can be maintained to a desirable level by choosing an appropriate proportion of C and M.
- The transient values of the performance indices stabilize after a certain time period. This indicates that the performance of the network becomes stable as time passes so that there is neither further improvement nor degradation.
- The results obtained by adaptive neuro fuzzy inference systems are quite closer to the numerical results.

7. Conclusion

In this investigation, we have modeled the behavior of a slotted aloha protocol for a wavelength division multiple access photonic network, using a semi-markov process. Steady state as well as transient models are developed for analyzing the protocol. The performance measures are studied with the variations in the number of interconnected nodes and the number of channels in the network. It is shown that the retransmissions of the packets can be reduced considerably if sufficient number of channels is provided in comparison to the number of nodes in the network. A certain level of performance can be maintained in the network if the number of channels is increased proportionally to the number of nodes.

We have assumed that at each node, only one packet is generated in a slot and the transmitter can transmit only one packet at a time. Our work can be further extended to a network where, multiple packets are generated in one slot and the transmitter also can transmit more than one packet, at a time. Another interesting extension may be the consideration of individual and common cause failures and repairs of the nodes in the network.

We have used neuro-fuzzy systems for obtaining the performance measures of the photonic network. It is shown that the results determined by the neuro fuzzy technique are at par with the numerical results obtained. We conclude that neuro-fuzzy systems provide an easy and fast solution technique for our system. Neuro-fuzzy systems can be further used for designing traffic controllers for the advanced photonic networks.

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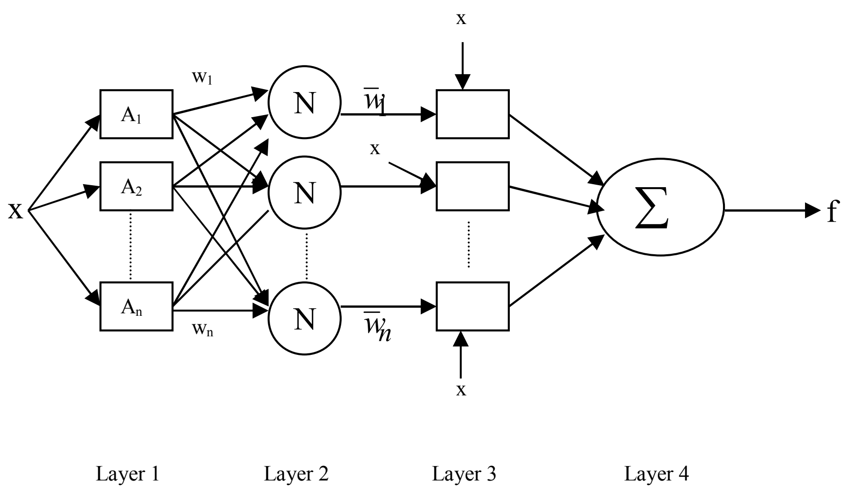


Fig. 1: ANFIS network architecture

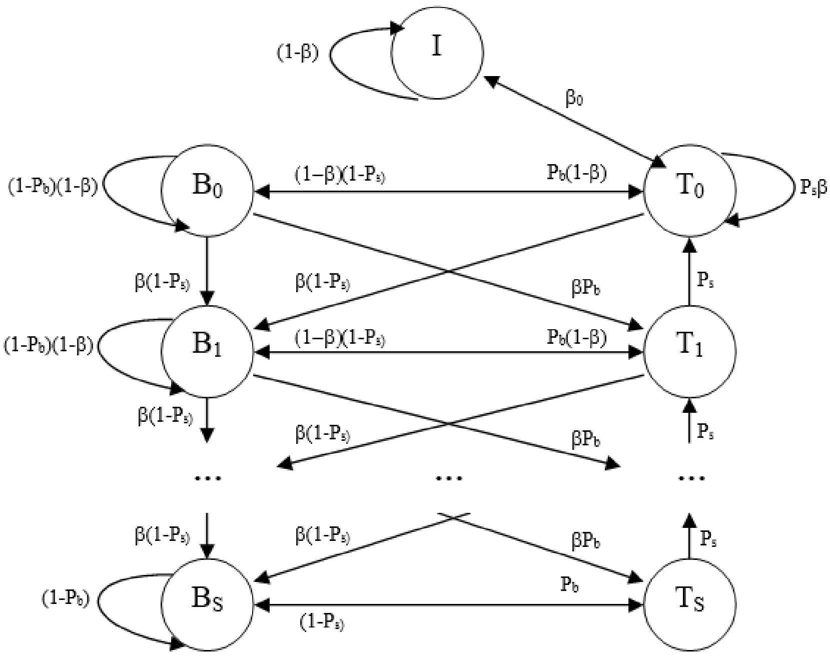


Fig.2: State transition diagram for the transmitter of a node

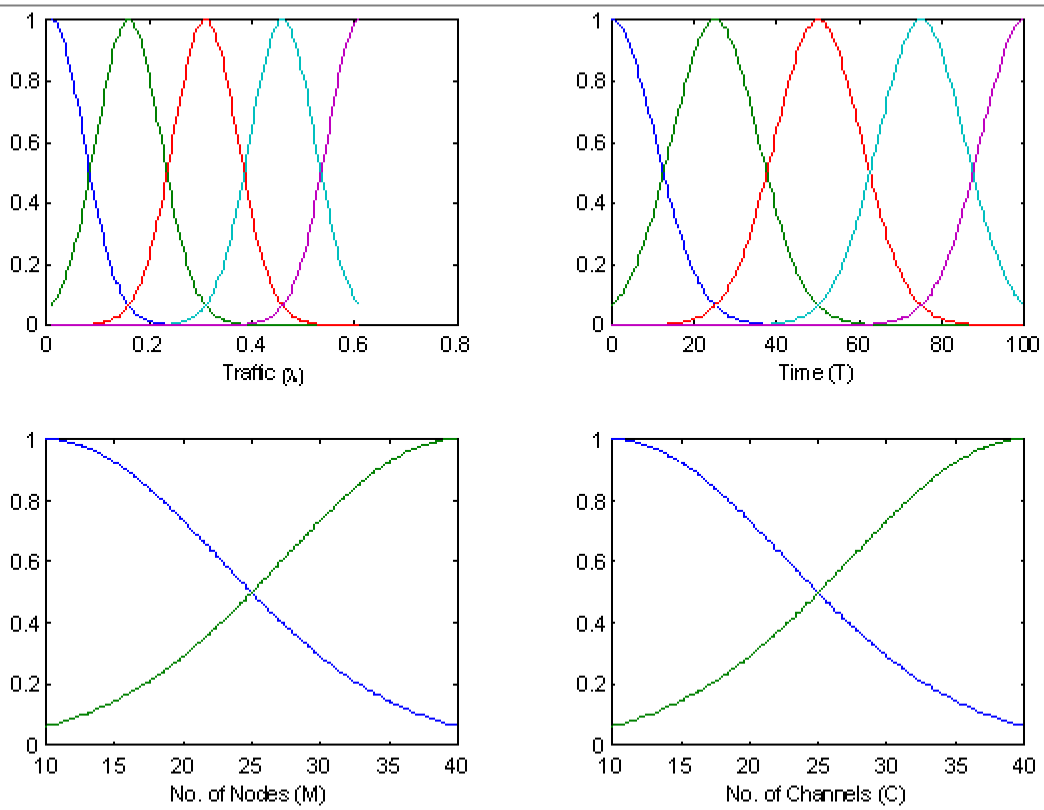
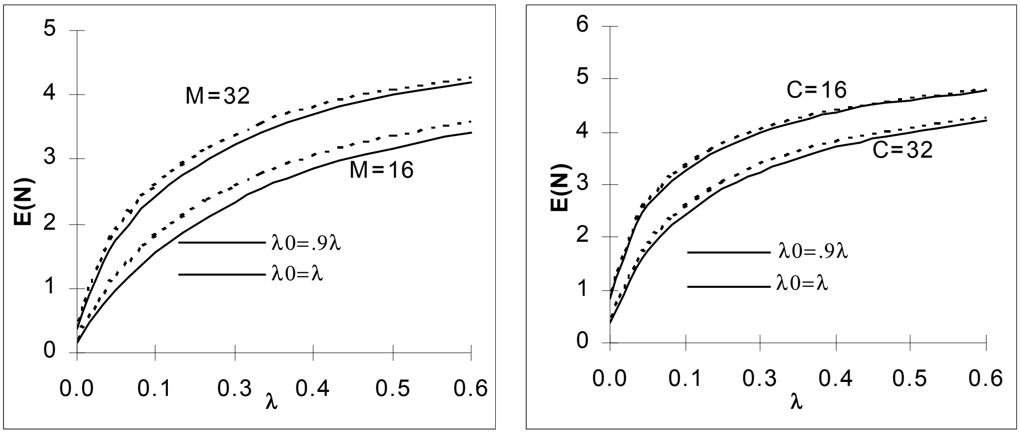
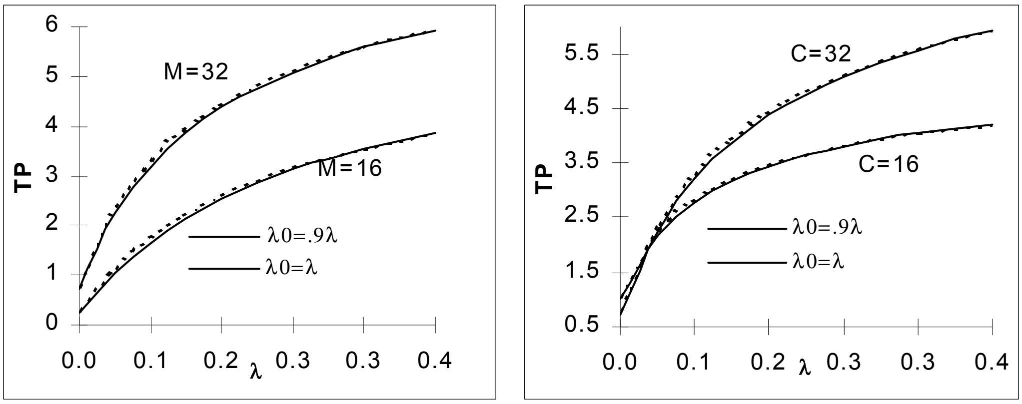


Fig. 3: Membership functions for the input variables λ, T, M and C



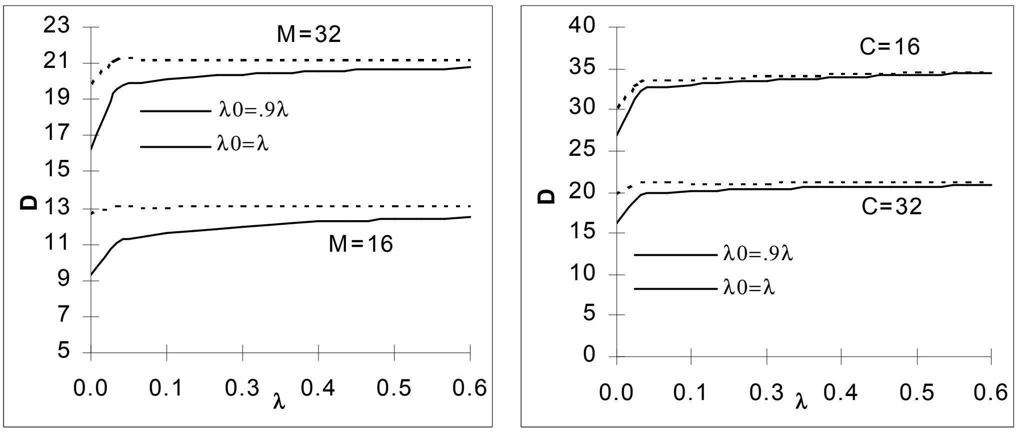
(a) **(b)**

Fig. 4: E(N) by varying λ for different values of M and C



(a) **(b)**

Fig. 5: Throughput by varying λ for different values of M and C



(a) **(b)**

Fig. 6: Average Delay by varying λ for different values of M and C

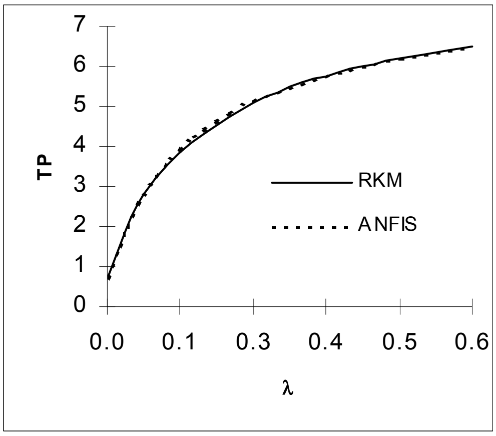


Fig. 7(a): RKM and ANFIS results for TP by varying λ

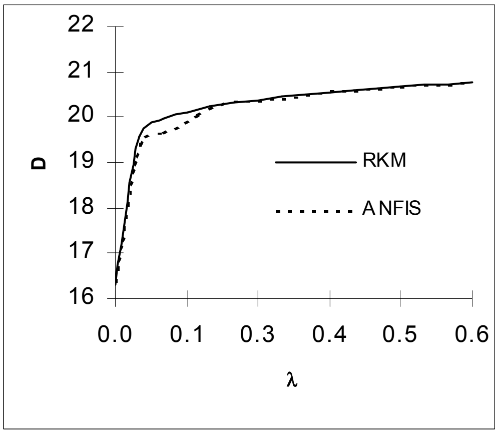


Fig. 8(a): RKM and ANFIS results for D by varying λ

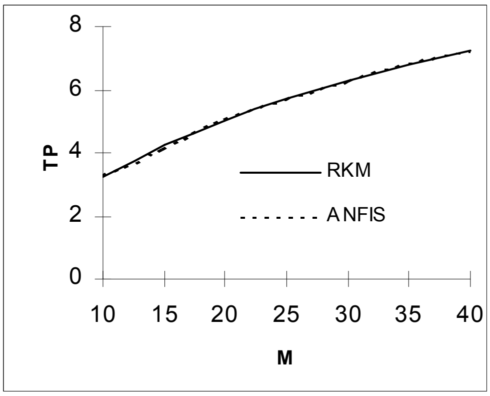


Fig. 7(b): RKM and ANFIS results for TP by varying M

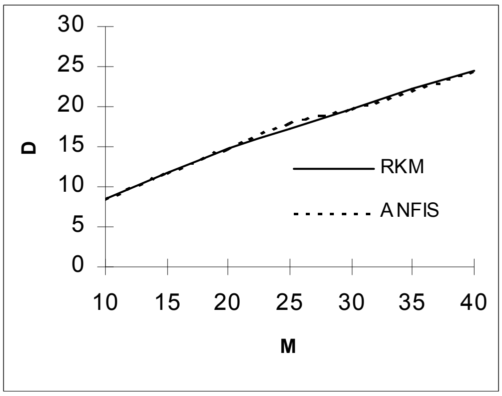


Fig. 8(b): RKM and ANFIS results for D by varying M

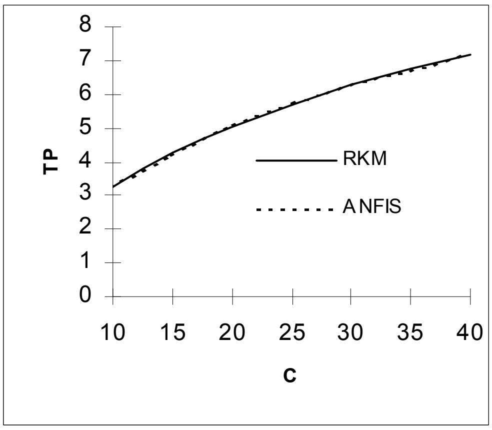


Fig. 7(c): RKM and ANFIS results for TP by varying C

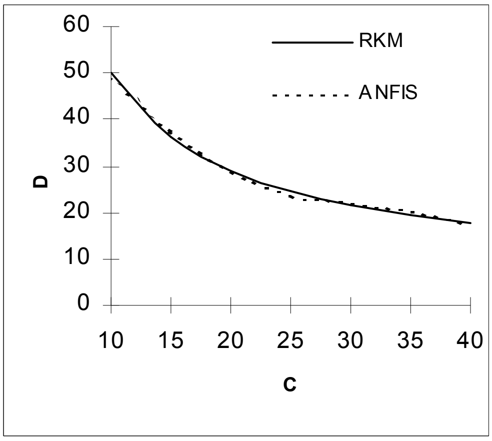


Fig. 8(c): RKM and ANFIS results for D by varying C

(λ=0.6,λ_0=0.9λ, C=32, M=32, Pb=0.05,S=5)

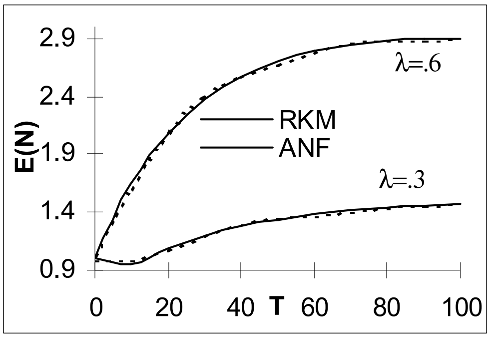


Fig. 9(a): Transient results for E(N) with varaitions in λ
(P_b=0.05,C=32, M=32, λ_0=0.9λ)

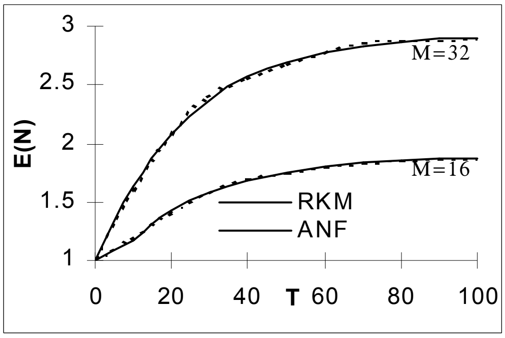


Fig. 9(b): Transient results for E(N) with varaitions in M
(P_b=0.05,C=32, λ=0.6, λ_0=0.9λ)

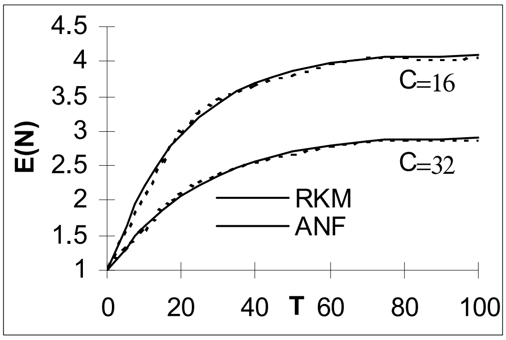


Fig. 9(c): Transient results for E(N) with varaitions in C
(P_b=0.05,M=32, λ=0.6, λ_0=0.9λ)

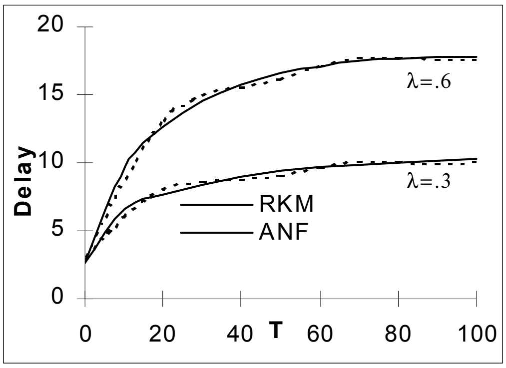


Fig. 10(a): Transient results for D with varaitions in λ
(P_b=0.05,C=32, M=32, λ_0=0.9λ)

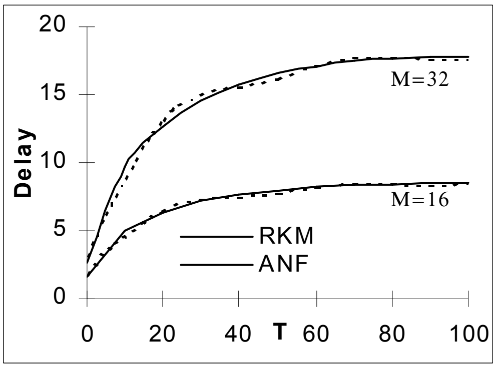


Fig. 10(b): Transient results for D with varaitions in M
(P_b=0.05,C=32, λ=0.6, λ_0=0.9λ)

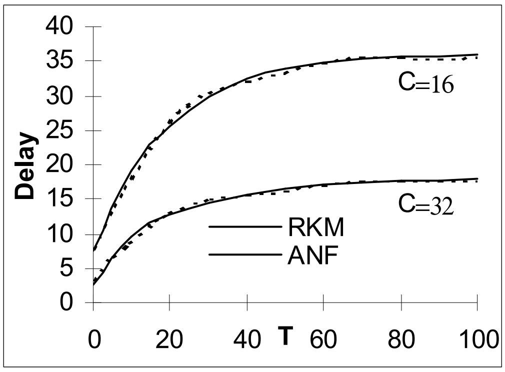


Fig. 10(c): Transient results for D with varaitions in C
(P_b=0.05,M=32, λ=0.6, λ_0=0.9λ)

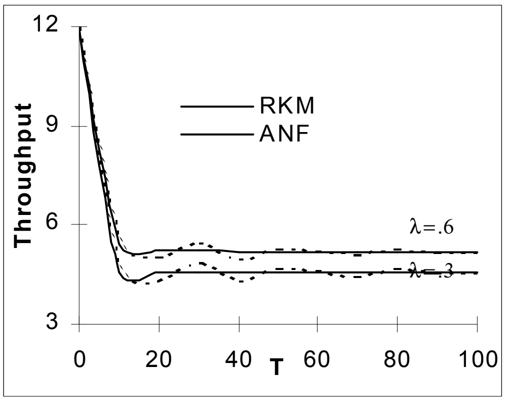


Fig. 11(a): Transient results for Throughput with varaitions in λ
(P_b=0.05,C=32, M=32, λ_0=0.9λ)

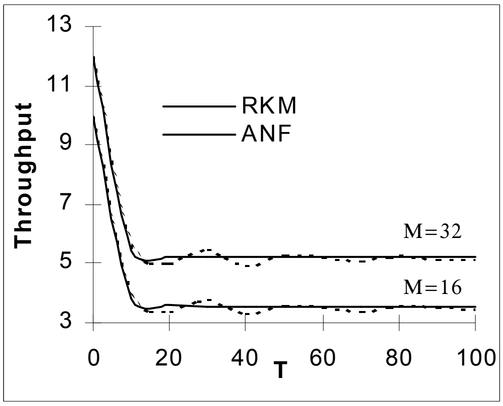


Fig. 11(b): Transient results for Throughput with varaitions in M
(P_b=0.05,C=32, λ=0.6, λ_0=0.9λ)

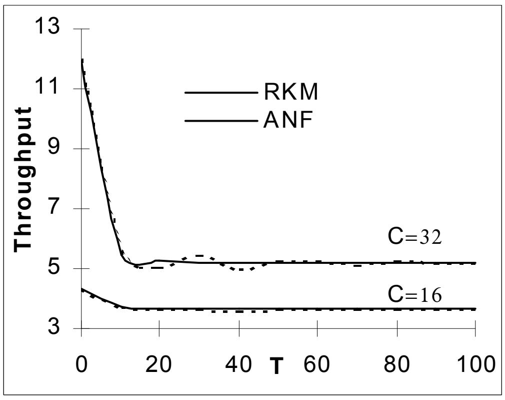


Fig. 11(c): Transient results for Throughput with varaitions in C
(P_b=0.05,M=32, λ=0.6, λ_0=0.9λ)

Table 2: Backoff and Transmit state probabilitiesfor steady state model by varying λ

	C=32,M=32				C=32,M=16				C=16,M=32			
	Ptransmit	Pbackoff	Ptransmit	Pbackoff	Ptransmit	Pbackoff	Ptransmit	Pbackoff	Ptransmit	Pbackoff	Ptransmit	Pbackoff
0.01	0.025125	0.221614	0.02263	0.198467	0.018385	0.106926	0.015917	0.088581	0.035568	0.405925	0.033642	0.386585
0.05	0.079918	0.465412	0.076391	0.443866	0.074181	0.295575	0.0688	0.265063	0.082477	0.628228	0.080479	0.61684
0.09	0.114857	0.536823	0.111332	0.517844	0.115715	0.370192	0.109832	0.339023	0.108928	0.678793	0.106938	0.669414
0.13	0.141297	0.573238	0.138034	0.555951	0.149061	0.413037	0.143506	0.382402	0.128182	0.702609	0.126288	0.694307
0.17	0.162282	0.596138	0.159426	0.580211	0.176519	0.442054	0.171689	0.412437	0.14312	0.716923	0.141383	0.70938
0.21	0.179386	0.612225	0.176997	0.59752	0.199507	0.463511	0.195581	0.435078	0.155091	0.726692	0.153545	0.719763
0.25	0.193598	0.624318	0.191675	0.610619	0.219028	0.480236	0.216059	0.453058	0.164892	0.73392	0.163536	0.727395
0.29	0.205603	0.633921	0.20412	0.621028	0.235817	0.493734	0.233786	0.467829	0.173057	0.739491	0.17191	0.733461
0.33	0.21586	0.641642	0.214796	0.629564	0.25042	0.504901	0.249271	0.480257	0.179938	0.743982	0.178997	0.738385
0.37	0.224723	0.647959	0.224047	0.636727	0.263252	0.514311	0.262909	0.490902	0.185801	0.747635	0.185056	0.742486
0.41	0.232468	0.653388	0.232127	0.642746	0.274628	0.522356	0.275006	0.500144	0.190863	0.750785	0.19028	0.745959
0.45	0.239288	0.65805	0.23925	0.648056	0.284793	0.529314	0.285807	0.508257	0.195255	0.753485	0.194821	0.748954
0.49	0.245337	0.662101	0.245564	0.65271	0.29394	0.535392	0.295505	0.515443	0.199092	0.755828	0.198794	0.751574
0.53	0.250738	0.665655	0.251193	0.656826	0.302221	0.540745	0.304259	0.521856	0.202469	0.757878	0.202291	0.75389
0.57	0.255588	0.6688	0.256237	0.660496	0.309759	0.545493	0.312197	0.527615	0.205458	0.759694	0.205386	0.755954
0.61	0.259965	0.671604	0.260778	0.663789	0.316653	0.549731	0.319425	0.532817	0.208118	0.761317	0.208136	0.757807