A Neural-Based MAC Protocol for Distributed Wireless LANs

P.Nicopolitidis$^+$ G.I.Papadimitriou$^+$ A.S.Pomportsis$^+$ and M.S.Obaidat *
$^+$ *Department of Informatics, Aristotle University, Box 888, 54124 Thessaloniki, Greece.*
* *Department of Computer Science, Monmouth University, USA.*
email: obaidat@monmouth.edu

Abstract – *A a self-adaptive neural-based MAC protocol for distributed wireless LANs, capable of operating efficiently under bursty traffic conditions, is introduced. According to the proposed protocol, the mobile station that is granted permission to transmit is selected by means of a neural-based algorithm. The neural-based algorithm takes into account the network feedback information in order to update the choice probability of each mobile station. The proposed protocol is compared via simulation to TDMA and is shown to exhibit superior performance under bursty traffic conditions even when the network feedback is noisy.*

Keywords: Wireless LAN, adaptive MAC protocol, neural network.

1 Introduction

There are fundamental differences between wireless [1] and wired LANs that pose difficulties in the design of Medium Access Control (MAC) protocols [2, 3, 4, 5, 6] for wireless LANs. Wireless LANs, as the name suggests, utilize wireless transmission for information exchange. The wireless medium is characterized by bit error rates (BER) having an order of magnitude even up to 10 times the order of magnitude of a LAN cable's BER. The primary reason for the increased BER is atmospheric noise, physical obstructions found in the signal's path, multipath propagation, interference from other systems and terminal mobility. Furthermore, in wireless LANs errors occur in bursts, whereas in traditional wired systems errors appear randomly. Finally, a fully connected topology between the nodes of a Wireless LAN cannot be assumed. Rather, the logical topology of a wireless LAN tends to change as users move from one position to another. As a result, wireless LANs are characterized by unreliable links between nodes resulting in bursts of errors and dynamically changing network topologies.

MAC protocols can be roughly divided into three categories: Fixed assignment (e.g. TDMA, FDMA), random access (e.g. ALOHA, CSMA/CD, CSMA/CA) and demand assignment protocols (e.g. token passing, polling). Fixed assignment protocols exhibit high performance when the traffic of each station is stable and the network topology remains unchanged. However, they fail to adapt to changes in network topologies and traffic and thus exhibit low performance when used over the wireless medium or under bursty traffic conditions. Random access protocols on the other hand, operate efficiently both without topology knowledge and under changing traffic characteristics. Nevertheless, their disadvantage is their non-deterministic behavior, a fact that causes problems in supporting QoS guarantees. Demand assignment protocols try to combine the advantages of fixed and random access protocols. However, the token-based approach is generally thought to be inefficient. This is due to the fact that in a Wireless LAN token losses are much more likely to appear due to the increased BER of the wireless medium. Furthermore, in a token passing network, the token holder needs accurate information about its neighbors and thus of the network topology. Polling, on the other hand, is a more appealing MAC option for a wireless LAN since it offers centralized supervision of the network nodes. However, constant monitoring of all nodes is required, which is not feasible in the harsh fading environment of a wireless LAN.

This paper proposes a self-adaptive neural-based MAC protocol (SANP))for distributed wireless LANs. According to the proposed protocol, the mobile station that is granted permission to transmit is selected via a neural-based algorithm, which is used to train the system in order to adapt to the network traffic pattern. The neural-like training algorithm utilizes a probability distribution vector, which contains the choice probability for each mobile station in the network. The network feedback plays the role of the system tutor. Following the reception of the feedback after a packet transmission, the neural algorithm performs a simple training procedure in order to reach the goal of ”learning” the transmission probabilities of the mobile stations. It is proved that the training algorithm asymptotically assigns to each station a portion of the bandwidth proportional to its needs.

The remainder of this paper is organized as follows: In Section 2, the operation of the SANP protocol is presented. Section 3 presents an analysis of the asymptotic behavior of the system. Section 4 details the simulation environment used to compare the relative performance of SANP to that of TDMA and presents simulation results that reveal SANP superiority in cases of medium and high loads in bursty-traffic networks. Finally, concluding remarks are presented in Section 5.

2 The SANP protocol

The neural-like training algorithm utilizes a probability distribution vector, which contains the choice probability Π_i for each mobile station u_i in the network. System training occurs as follows: After the network feedback, which plays the role of the system tutor, is received for the transmission at slot t, at each station u_i the basic choice probabilities are normalized in the following way:

$$\Pi_i(t) = \frac{P_i(t)}{\sum_{k=1}^{N} P_k(t)} \tag{1}$$

Clearly, $\sum_{i=1}^{N} \Pi_i(t) = 1$, where N is the number of mobile stations. In the beginning of slot t, the normalized probabilities $\Pi_i(t)$ are used to grant permission to transmit to a mobile station.

At each time slot t, the training procedure alters the choice probability of the selected station u_i according to the network feedback information. If station u_i transmitted a packet during slot t, then its basic choice probability is increased. Otherwise, if station u_i was idle, its basic choice probability is decreased. Thus:

$$\begin{aligned} &P_i(t+1) = P_i(t) + L(1 - P_i(t)),\\ &\text{if } u(t) = u_i \text{ and } SLOT(t) = SUCCESS \\ \\ &P_i(t+1) = P_i(t) - L(P_i(t) - a),\\ &\text{if } u(t) = u_i \text{ and } SLOT(t) = IDLE \end{aligned} \tag{2}$$

For all t, it holds that $L, a \in (0,1)$ and $P_i(t) \in (a,1)$. L governs system training speed and the selection procedure for a value of L reflects the classic speed versus accuracy problem. The lower the value of L the more accurate the estimation made by the algorithm, a fact however that comes at expense over convergence speed. The role of parameter a is to enhance the adaptivity of the protocol. This is because when the choice probability of a station approaches zero, then this station is not selected for a long period of time. During this period, it is probable that the station transits from idle to busy state. However, since the mobile station does not grant permission to transmit, the algorithm is not capable of ”sensing” such transitions. Thus, the use of a non-zero value for parameter a prevents the choice probabilities of the stations from taking values in the neighborhood of zero and increases the adaptivity of the protocol.

In a noiseless environment, SANP is collision-free, as all stations use the same protocol and due to the broadcast nature of the wireless medium the network feedback is common for all stations. Therefore, the protocol is collision-free despite its distributed nature since at each slot, all stations choose the same station to be granted permission to transmit.

However this is not true when the network feedback is not common for all stations. In these cases the choice probabilities values may be different at several stations and thus collisions may occur since it is likely that two or more stations may sometimes not grant permission to transmit to the same station. In such a situation, the wireless channel can be in one of the following three states:

- successful transmission
- collision
- idle

The simulation results that are presented in this paper assume the following situations can arise:

1. A ”successful” slot is perceived by a station as ”idle”, due to the fact that this station is out of range of the transmitting one
2. A ”successful” slot is perceived by a station as a ”collision” one, due to bit errors imposed by the wireless channel
3. A ”collision” slot is perceived by a station as ”successful”, due to the power capturing phenomenon
4. A ”collision” slot it perceived by a station as ”idle”, due to the fact that this station is out of range of the transmitting ones.

In order to avoid collisions, the probability distribution vectors at the various network nodes must not greatly differ. Thus, after each transmission performed, SANP piggybacks the K largest probabilities in the station’s data packet and the rest of the probabilities, which obviously concern stations that are not likely to transmit at this time, take the value of a. It is obvious that even with this mechanisms, collisions will occur again due to the noisy wireless network feedback. However this time the dissemination of the probability distribution vector between the network stations produces commonality among the values of the various probability vectors that correspond to those stations that are likely to transmit. This mechanism leads to fewer collisions

It is obvious that the selection for the value of K depends on the number of stations. If the network comprises a large number of stations N, then a selection for K with $K < N$ will limit the overhead caused by the protocol. The simulation results presented later in the paper reveal that this mechanism leads to a satisfactory performance for the protocol.

3 Asymptotic Analysis

The SANP protocol updates the choice probabilities of mobile stations according to the network feedback information. In the present section we will prove that the choice probability each mobile station converges to the probability that this station is ready to transmit. Thus, it has a non-empty queue. The following theorem (presented in [7]) is needed to carry out the asymptotic analysis:

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

$$\sup_{y\in I}\frac{O(\theta^k)}{\theta^k}<\infty \text{ for } k=2,3 \quad\text{and}\quad \sup_{y\in I}\frac{O(\theta^2)}{\theta^2}\to 0 \text{ as } \theta\to 0$$

(v) $\omega(y)$ has a Lipschitz derivative in I.
(vi) $b(y)$ is Lipschitz in I.

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

Theorem 2: Under the SANP protocol, the choice probability of a mobile station k_i converges to the probability that station k_i is ready to transmit. If the learning algorithm (2) is used and d_i is the probability that station k_i is ready (for $i = 1, \ldots, N$), then for any station k_i:

$$\lim_{n\to\infty, L\to 0, a\to 0} P_i(n) = d_i$$

Proof. We use Theorem 1 to the proof of the current theorem. Here we have to identify $x(n)$ (of Theorem 1) with $P_i(n)$, θ (of Theorem 1) with L and I (of Theorem 1) with $(a,1)$. We have:

$$\begin{aligned}&E[\delta P_i(n)|P_i(n)=P_i]\\ &= \frac{P_i}{\sum_{k=1}^N P_k}(d_i L(1-P_i) - (1-d_i)L(P_i - a))\\ &= L\frac{P_i}{\sum_{k=1}^N P_k}(-P_i + d_i + a(1-d_i)) = L\omega(P_i)\end{aligned} \tag{3}$$

$$\begin{aligned}&E[|\delta P_i(n)|^2|P_i(n)=P_i]\\ &= L^2\frac{P_i}{\sum_{k=1}^N P_k}(d_i(1-P_i)^2 + (1-d_i)(P_i-a)^2) = L^2 b(P_i)\end{aligned} \tag{4}$$

$$\begin{aligned}&E[|\delta P_i(n)|^3|P_i(n)=P_i]\\ &= L^3\frac{P_i}{\sum_{k=1}^N P_k}(d_i(1-P_i)^3 + (1-d_i)(P_i-a)^3) = O(L^3)\end{aligned} \tag{5}$$

The functions $\omega(P_i)$ and $b(P_i)$ are defined as follows:

$$\omega(P_i) = \frac{P_i}{\sum_{k=1}^N P_k}(-P_i + d_i + a(1-d_i)) \tag{6}$$

$$b(P_i) = \frac{P_i}{\sum_{k=1}^N P_k}(d_i(1-P_i)^2 + (1-d_i)(P_i-a)^2) \tag{7}$$

It is immediately seen that assumptions (i)-(iv) are satisfied. It can also be proved that $b(P_i)$ and $\omega'(P_i)$ are Lipschitz in (a,1) by showing that their first derivatives ($b'(P_i)$ and $\omega''(P_i)$ correspondingly) are bounded [8] for $P_i \in (a,1)$.

It remains to show that $\omega(P_i)$ has a unique root P_i^r near the point $P_i^* = d_i$ and that $d\omega(P_i)/dP_i|_{P_i=P_i^r} < 0$. It is immediately seen that $\omega(P_i)$ has a unique root at the point $P_i^r = d_i + a(1-d_i)$. Since a can be arbitrarily small, it follows that P_i^r is in the neighborhood of the point $P_i^* = d_i$. The derivative of $\omega(P_i)$ at this point is:

$$\begin{aligned}\frac{d\omega(P_i)}{dP_i}\Big|_{P_i=P_i^r} &= \frac{d\left(\frac{P_i}{\sum_{k=1}^N P_k}(-P_i+d_i+a(1-d_i))\right)}{dP_i}\Big|_{P_i=P_i^r}\\ &= -\frac{1}{1+\frac{\sum_{k=1,k\neq i}^N P_k}{P_i^r}} < 0\end{aligned} \tag{8}$$

It has been shown that $\omega(P_i)$ has a unique root P_i^r in the neighborhood of the point $P_i^* = d_i$ and that the derivative of $\omega(P_i)$ at this point is negative.

If we set $P_i(\tau) = P_i^r$, the differential equation $\frac{dP_i(\tau)}{d\tau} = \omega(P_i(\tau))$ is satisfied (0=0). Thus, $P_i(\tau) = P_i^r$ is a solution of the above differential equation. From Theorem 2, it is derived that this solution is unique, thus all the solutions starting in $(a,1)$ of the differential equation $\frac{dP_i(\tau)}{d\tau} = \omega(P_i(\tau))$ converge to the point $P_i(\tau) = P_i^r \simeq P_i^* = d_i$. According to Theorem 2, we have:

$$\lim_{n\to\infty, a\to 0} E[P_i(n)] = P_i^* + O(L)$$

and

$$var[P_i(n)] = O(L) \qquad \text{for all } n.$$

Consequently,

$$\lim_{n\to\infty, L\to 0, a\to 0} P_i(n) = d_i \qquad \text{q.e.d.} \tag{9}$$

The exact values of a and L depend on the environment where the system operates. When the environment is slowly switching or when the environmental responses have a high variance, a and L must be very close to 0 in order to guarantee a high accuracy. On the other hand, in a rapidly switching environment or when the variance of the environmental responses is low, higher values of a and L can be used, in order to increase the adaptivity of the protocol. Thus, when the burst length is high or the queue length is low, then small values of a and L must be selected. On the other hand, when

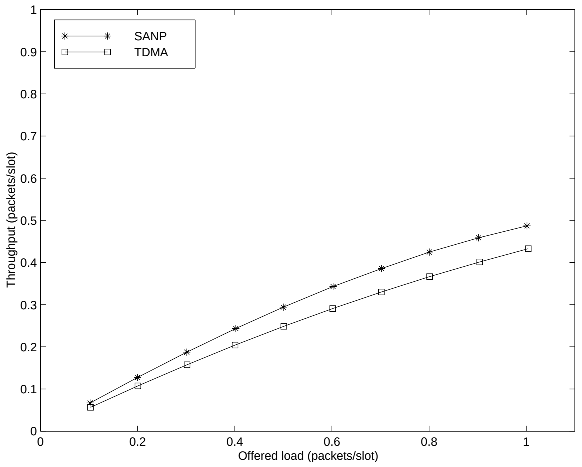

Figure 1: The Throughput versus Offered load characteristics of SANP and TDMA when applied to network N_1.

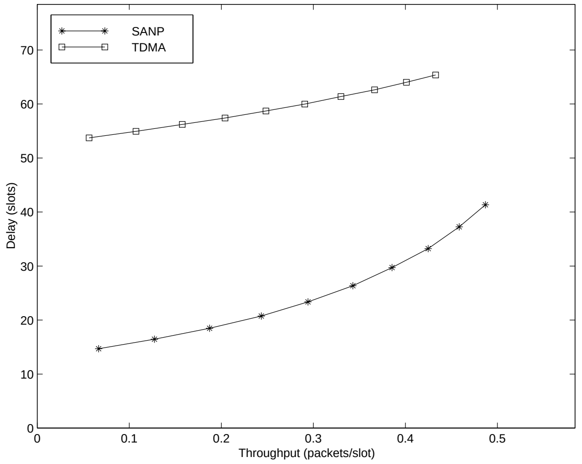

Figure 2: The Delay versus Throughput characteristics of SANP and TDMA when applied to network N_1.

the burst length is low or when the queue length is high, then a and L can be much higher.

According to Theorem 2, for any two mobile stations k_i and k_j (with $d_j \neq 0$), the SANP protocol asymptotically tends to satisfy the relation:

$$\frac{P_i}{P_j} = \frac{d_i}{d_j} \tag{10}$$

This relation also holds for the normalized choice probabilities Π_i and Π_j:

$$\frac{\Pi_i}{\Pi_j} = \frac{\frac{P_i}{\sum_{k=1}^{N} P_k}}{\frac{P_j}{\sum_{k=1}^{N} P_k}} = \frac{P_i}{P_j} = \frac{d_i}{d_j} \tag{11}$$

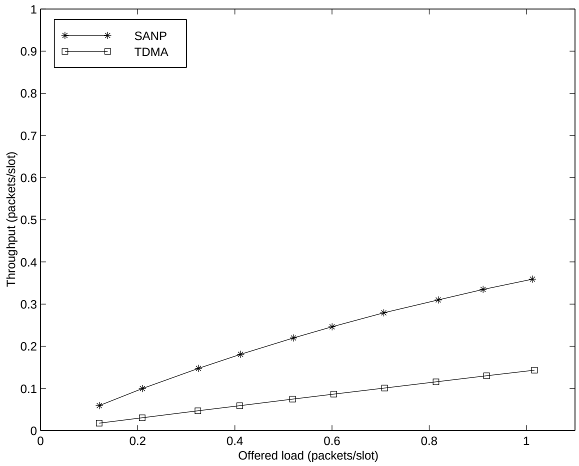

Figure 3: The Throughput versus Offered load characteristics of SANP and TDMA when applied to network N_2.

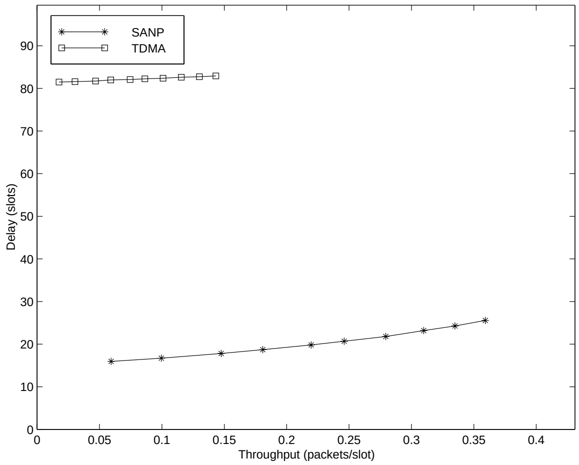

Figure 4: The Delay versus Throughput characteristics of SANP and TDMA when applied to network N_2.

4 Simulation results

Using simulation, we compared SANP against TDMA. The bursty traffic was modeled in the following way: We define ”time slot” as the time duration required for a data packet to be transmitted. Each source node can be in one of two states, S_0 and S_1. When in state S_0 then it has no packet arrivals. When in state S_1 then, at each time slot, the station 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: $P_{01} = \frac{R}{B(NZ-R)}$ and $P_{10} = \frac{1}{B}$. Each station uses a Q-sized buffer to store arriving packets. Any packets arriving to find the buffer full, are dropped.

In our simulation model, the condition of the wireless link between any two stations was modeled using a finite state machine with three states. Such structures can efficiently approximate the behavior of a wireless channel [9, 10] and are widely used in simulations. The model comprises two states and four parameters:

- Stage G, denotes that the wireless link is in a relatively ”clean” condition and is characterized by a small BER, which is given by the parameter $GOOD\_BER$
- Stage B, denotes that the wireless link is in a condition characterized by increased BER, which is given by the parameter BAD_BER

We assume that the background noise is the same for all stations and thus the principle of reciprocity stands for the condition of any wireless link. Therefore, for any two stations A and B, the BER of the link from A to B and the BER of the link from B to A are the same. The time periods spent by a link in states G and B are exponentially distributed, but with different average values, given by the parameters TG and TB. The status of a link probabilistically changes between the two states. When a link has spent its time in state G, the link transits either to stage B. When a link has spent its time in state B, the link transits to stage G.

We employed the broadly used a) throughput versus offered load and b) delay versus throughput performance metrics in order to compare the three protocols. We simulated the protocols for the following two different network configurations:

1. Network N_1: N=10, Q=10, B=10, Z=1.
2. Network N_2: N=10, Q=10, B=100, Z=1.

In these simulations, the following parameter values remain constant: G_BER=10^{-10}, B_BER=10^{-4}, TG= 30 sec, TB=10 sec, $k = 5$, R_LIM=1 and $P_c = 0.1$, $P_i = 0.1$. R_LIM sets the maximum number of retransmission attempts per packet. P_c is the probability that when two or more data packets collide, one of them is successfully decoded at the destination station due to the power capture phenomenon. P_i is the probability that each transmission does not get through to a certain station, thus this stations perceives the slot as idle. Finally, the DATA packet size is set to 1000 bits. The wireless medium bit rate was set to 1 Mbps and the propagation delay between any two stations was set to 0.0005 msec corresponding to inter-station distances of 150 meters.

Figures 1-4 display simulation results that reveal the performance superiority of SANP over TDMA. In general, the results we obtained show that the burstier the traffic, the more increased the superiority of SANP over TDMA.

5 Conclusion

Modern WLAN MAC protocols should be able to efficiently handle the bursty traffic that is expected to be generated by WLAN applications. This paper proposes SANP, a self-adaptive neural-based MAC protocol for distributed wireless LANs. According to the proposed protocol, the mobile station that is granted permission to transmit is selected via a neural-based algorithm, which is used to train the system in order to adapt to the network bursty traffic pattern. The neural-like training algorithm utilizes a probability distribution vector, which contains the choice probability for each mobile station in the network. After the network feedback, which plays the role of the system tutor, is received for a transmission, the system trains a probability distribution vector in order to reflect the transmission probabilities of the mobile stations. It is proved that the training algorithm asymptotically assigns to each station a portion of the bandwidth proportional to its needs. The protocol is able to achieve significantly higher throughput and lower delay values compared to TDMA under bursty traffic conditions in wireless environments. The main characteristics of SANP are:

1. It achieves a high performance, even when the offered traffic is bursty and the network feedback is noisy.
2. It is self-adaptive. Each station is assigned a fraction of the bandwidth proportional to its needs.
3. It is fully distributed, thus no centralized control of the network is required.
4. Due to its distributed nature, it is fault-tolerant, since its operation is not affected from a station failure.
5. It is very simple to implement. The only extra requirement over TDMA is the existence at of a processor at each station, which implements the neural algorithm.

References

[1] P. Nicopolitidis, M. S. Obaidat, G. I. Papadimitriou and A. S. Pomportsis, *Wireless Networks*, John Wiley and Sons Ltd., 2003.

[2] P.Nicopolitidis, G.I.Papadimitriou and A.S.Pomportsis, ”Learning Automata-Based Polling Protocols for Wireless LANs”, *IEEE Transactions on Communications*, vol.51, no.3, March 2003, pp. 453-463.

[3] P.Nicopolitidis, G.I.Papadimitriou and A.S.Pomportsis, ”Self-Adaptive Polling Protocols for Wireless LANs: A Learning-Automata-Based Approach”, *in Proceedings of IEEE International Conference on Electronics, Circuits and Systems (ICECS) 2001*, September 2-5 2001, Malta, pp. 1309-1312.

[4] P.Nicopolitidis, M.S.Obaidat, G.I.Papadimitriou and A.S.Pomportsis, ”TRAP: a high performance protocol for wireless local area networks”, *Computer Communications*, Elsevier, vol. 25, July 2002, pp. 1058-1065.

[5] P.Nicopolitidis, G.I.Papadimitriou, M.S.Obaidat and A.S.Pomportsis, ”A New Protocol for Wireless LANs”, *in Proceedings of IEEE International Conference on Communications (ICC) 2002*, 28 April - 5 May 2002, New York, USA, pp. 3434-3438.

[6] P.Nicopolitidis, G.I.Papadimitriou, M.S.Obaidat and A.S.Pomportsis, ”Performance Evaluation of a TDMA-based Randomly Addressed Polling Protocol for Wireless LANs”, *in Proceedings of IEEE International Conference on Electronics, Circuits and Systems (ICECS) 2002*, September 15-18 2002, Dubrovnik, Croatia, pp. 1047-1050.

[7] K.S.Narendra and M.A.L.Thathachar, ”On the behavior of a learning automaton in a changing environment with application to telephone traffic routing”, *IEEE Transactions on Systems, Man and Cybernetics*, vol.SMC-10, no.5, May 1980, pp.262-269.

[8] S.M.Nikolsky, *A Course of Mathematical Analysis*, MIR Publishers, Moscow 1977.

[9] E. Gilbert, ”Capacity of a burst noise channel”, *Bell System Technology Journal*, vol. 39, September 1960.

[10] Michelle Zorzi, Rarnesh R. Rao, Laurence B. Milstein, ”On the Accuracy of a first-order Markov model for data transmission on fading channels”, *n Proceedings of ICUPC 95*, Tokyo, Japan, November 1995.