A Learning Automata Based Power Management for Ad-Hoc Networks

Aly I. El-Osery, David Baird
Electrical Engineering Department
New Mexico Institute of Mining and Technology
Socorro, New Mexico 87801
Email: {elosery,dbaird}@ee.nmt.edu

Wael Abd-Almageed
Institute for Advanced Computer Studies
University of Maryland
College Park, MD 20742

Abstract— *Power management is a very important aspect of ad-hoc networks. It directly impacts the network throughput among other network metrics. On the other hand, transmission power management may result in disconnected networks and increased level of collisions. In this paper, we introduce a transmission power control based on stochastic learning automata (SLA) to modify the transmission power. Based on the level of successful transmissions and the level of packet retransmissions, the SLA will modify the transmission power level either by increasing it or decreasing it. The probabilistic nature of SLA makes it a useful choice for ad-hoc networks. Using the network simulator NS, we show that using SLA for transmission power will result in an increased system bandwidth and a decrease in the collision levels.*

Keywords— ad hoc networks, stochastic learning automta, power control

1. Introduction

Unlike conventional wireless networks which require, as a prerequisite, a fixed network infrastructure, ad-hoc networks consists of dynamically interacting wireless nodes that may be mobile without an infrastructure or centralized support [1]. Ad-Hoc networks are suited for many applications ranging from infrastructureless networks of computers in a campus setting to sensors scattered throughout a city for biological detection. Scalability and self sufficiency are very desirable features. Consequently, and due to the limitations in resources, i.e., bandwidth and power, power management is a must in the design of ad-hoc networks. By designing a powerful power control algorithm that maintains network connectivity, reduces interference, prolongs battery lifetime, and increases system throughput, implementation of large ad-hoc networks will become more reliable, practical, and robust. As the number of nodes in the network increase, become mobile, and the network topology becomes dynamic, the power control problem complexity increases.

In [2], the authors incorporated power control into the IEEE 802.11 protocol. The authors utilized the IEEE 802.11 RTS-CTS handshaking to send power level information. A node sending the RTS will attach to the message its transmission power level. The receiving node will use this information and send back a CTS message with the desired transmission power level. Then the DATA is sent using the new power level. With this power control approach, only the transmission power of the DATA is modified and the handshaking is transmitted with the maximum transmission power to avoid hidden nodes. This approach will be referred to as the BASIC power control.

In the case where the nodes are distributed homogeneously, a common power level is selected by COMPOW [3]. This power level is used by all nodes and is selected so as to maintain the network connectivity. A clustering approach to power control, CLUSTERPOW, is presented in [4]. In this approach, three different power levels are used for transmission. The selection of the power level is determined by the clustering of nodes. Since the power control is applied to both the data and the handshaking signals, collisions may occur if one of the nodes doesn't sense the presence of communication while attempting to transmit at a high power.

In [5] a power control algorithm similar to that developed in [6] is presented. In this technique a dynamic table with different power levels used to communicate with different nodes is maintained. This will help with accounting for the changes in the network topology.

None of the approaches mentioned above take into consideration the likelihood of communication or how often nodes communicate with each other. Therefore, these approaches are limited in scope and there is a room for improvement.

There are three fundamental yet critical issues in the design of power control.

1) As the transmission power is reduced, the communication range is reduced and may risk loosing network connectivity.
2) As the communication range is reduced, the number of hops per packet may also increase, and consequently, may increase system latency and decrease throughput.
3) As the transmission power is being increased or decreased, more collisions may occur due to incorrect assumptions about the usage of the channel.

This paper is organized as follows. In Section 2 we present our motivation to the presented approach. In Section 3 a brief overview of IEEE 802.11b is provided followed by an introduction to stochastic learning automata in Section 4. The simulation environment is outlined in Section 5. In Section 6, simulation results are presented. Finally, in Section 7 our conclusion is provided.

2. Motivation

With transmission power control, the communication range may be modified. As shown in Figure 1, nodes B and D are transmitting at a higher power than nodes F and H where the communication range is shown using circles. Based on the shown configuration, only nodes A and B may communicate or nodes C and D otherwise collisions may occur. On the other had, and due to the lower transmission power used by nodes F and H, both nodes E and F, and nodes H and G may communicate at the same time. Consequently, system throughput is increased. Of course, due to the lower transmission power used by node F, it is unable to reach nodes G and H, and thereby resulting in a disconnected network. Consequently, a mechanism has to be devised to adaptively change the transmission power to ensure network connectivity.

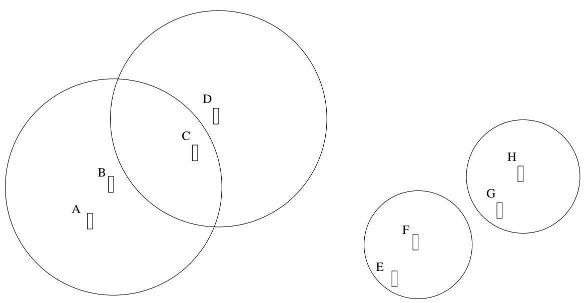

Fig. 1. Different communication range

Without loss of generality, we will assume that the network is formed for a specific purpose and that the communication is not frequent between every node and all of the other nodes in the network. Additionally, that nodes are non-homogeneously distributed. Based on this assumption, it is clear that using a maximum transmission power is not efficient, and yet, due to the unpredicted nature of the network, using a deterministic algorithm to modify the transmission power level is extremely complex, if at all possible. Hence, we propose the use of stochastic learning automata to modify the transmission power levels.

Studying of Learning Automata started in early Sixties [7] [8]. Learning automata theory provides a framework for the design of automata which interact with a random environment and dynamically learn the action that minimizes the probability of a penalty. Since the Sixties, this field has seen vast improvements and developments [9] [10]. The main advantage of SLA is that it does not require any knowledge about random environment in which the automaton operates, or the function to be optimized.

3. IEEE 802.11

In the design of the power control algorithm a signaling scheme similar to the IEEE 802.11b is assumed. As shown in Figure 2, a request-to-send (RTS) message is send first, if the receiving node is free, it will broadcast a clear-to-send (CTS) message. If the transmitting node hears the CTS, it will proceed to transmit its data (DATA), otherwise collision will be assumed and it will backoff for a certain amount of time before trying again. After DATA is transmitted, the receiving node will transmit an acknowledgment (ACK). Any node that can hear those signals, RTS CTS DATA ACK, will have some information about the occupation of the channel and for how long.

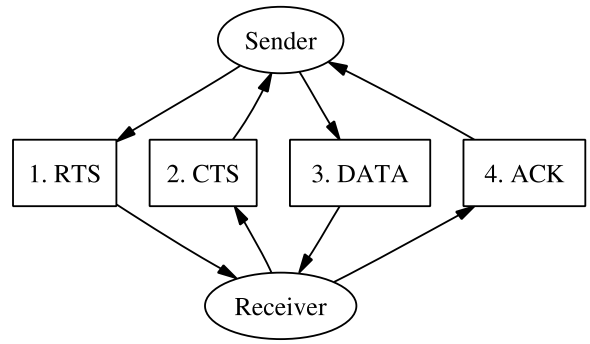

Fig. 2. Signaling scheme of the IEEE 802.11b

4. Stochastic Learning Automata

One main advantage of learning automaton is that it needs no knowledge of the environment in which it operates or any analytical knowledge of the function to be optimized. Learning automaton is a sequential machine characterized by a set of: internal states, input actions, state probability distributions, a reinforcement scheme, and an output function and is connected in feedback loop to the environment as shown in Figure. 3.

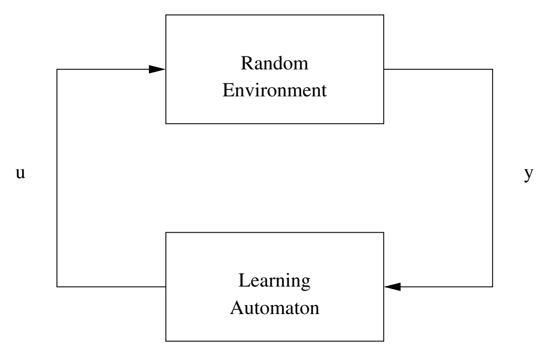

Fig. 3. Automaton operating in random environment

The probability distribution of the actions, P_{u_i}, is adjusted using reinforcement scheme to achieve the desired objective. At each step, the performance of the SLA through the environment is evaluated by either a penalty (or unsatisfactory performance) ($y = 1$), or a nonpenalty (or satisfactory performance) ($y = 0$). A stochastic automaton is a quintuple $\{Y, Q, U, F, G\}$ where

- If Y consists of only two elements 0 and 1, the environment is said to be *P-model*. When the input into the SLA is a finite number values in the closed interval [0,1], the environment is said to be *Q-model*. On the other hand, if the inputs are arbitrary numbers in the closed line segment [0,1], the environment is known as *S-model*,
- Q is a finite set of states, $Q = \{q_1, \ldots, q_s\}$,
- U is a finite set of outputs, $U = \{u_1, \ldots, u_m\}$,
- F is the next state function

$$q(n+1) = F[y(n), q(n)], \tag{1}$$

- and G is the output function

$$u(n) = G[q(n)]. \tag{2}$$

In general, the function F is stochastic and the function G may be deterministic or stochastic. Because of the stochastic nature in state transitions, stochastic automata are considered suitable for modeling learning systems. If the output of the automaton is $u_j, j = 1, 2, \ldots, m$, the random environment generates a penalty with probability τ_j or a nonpenalty with probability $(1 - \tau_j)$.

The reinforcement scheme used to update the probability distribution of action is as follows [11].

Assume that $u(n) = u_i$.
If $y(n) = 0$,

$$P_{u_i}(n+1) = (1-\alpha)P_{u_i}(n) + \alpha, \tag{3}$$

$$P_{u_j}(n+1) = (1-\alpha)P_{u_j}(n) \qquad (j \neq i) \tag{4}$$

If $y(n) = 1$,

$$P_{u_i}(n+1) = P_{u_i}(n) - v\alpha(1 - P_{u_i}(n))\left(\frac{H}{1-H}\right), \tag{5}$$

$$P_{u_j}(n+1) = P_{u_j}(n) + v\alpha P_{u_j}(n)\left(\frac{H}{1-H}\right), \quad (j \neq i) \tag{6}$$

where

$$H = \min[P_{u_1}(n), \ldots, P_{u_m}(n)], \tag{7}$$

$$0 < \alpha < 1, \tag{8}$$

$$0 < v\alpha < 1, \tag{9}$$

$$P_{u_1}(0) = \ldots = P_{u_m}(0) = \frac{1}{m} \tag{10}$$

The operation of the SLA is as follows. An action, i.e., increase or decrease transmission power, is selected at random; if the action results in a reward, its probability distribution is increased and the probability distributions of the other actions are decreased based on Equations 3 and 4. The learning rate is determined by α. On the other hand if the randomly selected action results in a penalty, its probability distribution is decreased and the probability distributions of the other actions are increased based on Equations 5 and 6. The penalty or reward is assigned based on the number of packet collisions If the collision level is low, a reward is given, otherwise the action is penalized.

5. Simulation Environment

The discrete event network simulation, NS version 2.27 [12], will be used. In 1995, NS development was supported by DARPA through the VINT project. Because of the CMU Monarch project extensions, NS supports the IEEE 802.11 MAC standard [13] which executes above a wireless RF (radio frequency) physical layer. The four different adhoc routing protocols currently implemented for mobile networking are DSDV, DSR, AODV and TORA [14]–[19]. NS is written using Tcl/C++.

A. Limitations

- No systems for adaptive control over transmission power.
- Interference model too simple
  - Assumes constant noise floor, regardless of active transmissions.
  - Collision only checks two power levels, not all power levels (the level of the packet being received and the interfering packet).

B. Modifications

- Hooked into the phy and mac layers.
- Added classes that allow convenient modulation of transmission power for power control purposes.
- Interference is now computed from all transmissions.
- For received packets, it is possible to determine the SIR for each individual packet.

6. Simulation Results

A scenario with 6 nodes has been created to test the use of the proposed power control algorithm. Due to the massive amount of data to be processed, strictly a simulator issue, the number of nodes was limited and used as a proof-of-concept. Each pair of nodes is located close together as shown in Figure 4. The node pairs 0-1 and 2-3 start communicating at time 5sec. Then at 10 seconds nodes 4-5 start communicating till time 40sec. The system was simulated without power control and with SLA based power control

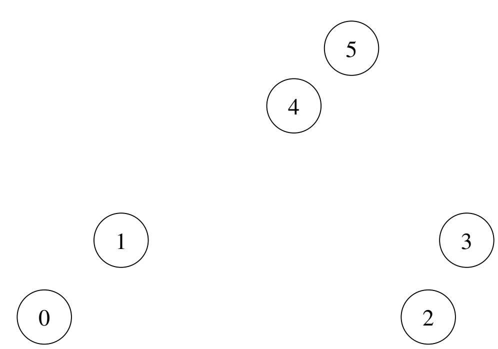

Fig. 4. Simulation scenario

Figures 5 and 6 show the bandwidth result of using no power control versus with power control. The measured data are as follows:

- transmit rate = sum(bits transmitted) / interval of time
- receive rate = sum(bits transmitted that were successfully received) / interval of time
- basic rate = sum(bits transmitted) / sum(packet durations)

In general, receive rate less than or equal to the transmit rate means not all transmitted data will be received. If receive rate is greater than basic rate then the bandwidth of the network is maximized (e.g. by lowering transmission powers so that nodes have a isolated/localized communication region).

As shown in Figure 5 the bandwidth of the system stays almost constant even when the pair 4-5 starts communicating. This is due to the high power of the handshaking signals. At a high transmission power all the nodes that hear the handshaking signals will refrain from communicating, unless the signals are intended for the that node, to reduce the probability of collisions. On the other hand using the SLA power control has resulted in an increase in the system bandwidth. The SLA adapts to the frequency of communication between the neighboring nodes and accordingly modifies the transmission power, Figure 6. If packets are received successfully and ACK is received the action of decreasing power is rewarded. On the other hand, if either RTS or DATA packets have to be retransmitted, then the action of increasing power is increased.

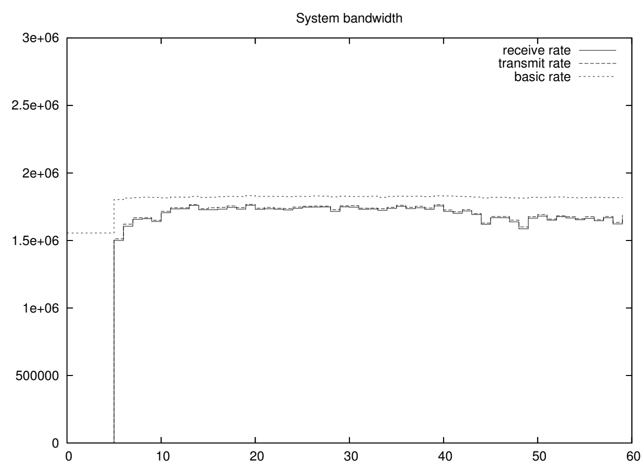

Fig. 5. System bandwidth without power control

Figures 7 and 8 show the rate of collision with and without power control. As seen in the figures, SLA reduces the collision rate will providing more bandwidth.

7. Conclusion

Power control has its advantages to ad-hoc networks. It has the potential to increase the system throughput, system capacity, reduce latency, and increase the battery lifetime. But, without careful design power control may produce the opposite results.

It is important to realize the design of power control is highly dependent on the system topology, and without having a mechanism to adapt to different network topologies, it is hard to generalize whether a given power control is effective or not.

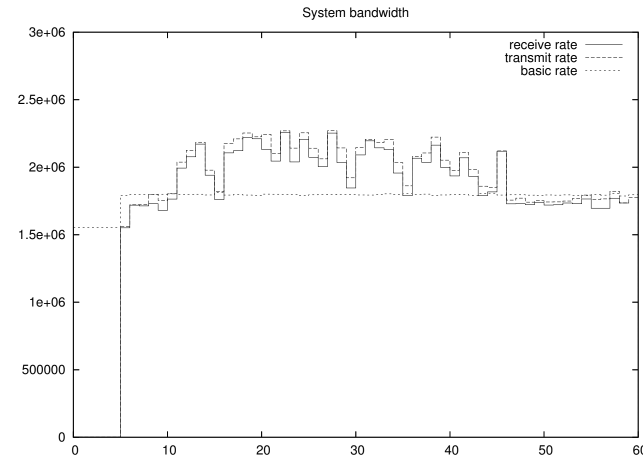

Fig. 6. System bandwidth with power control

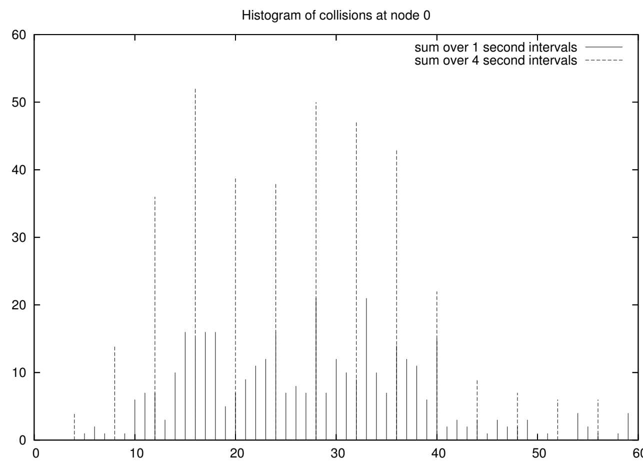

Fig. 7. Collision results without power control

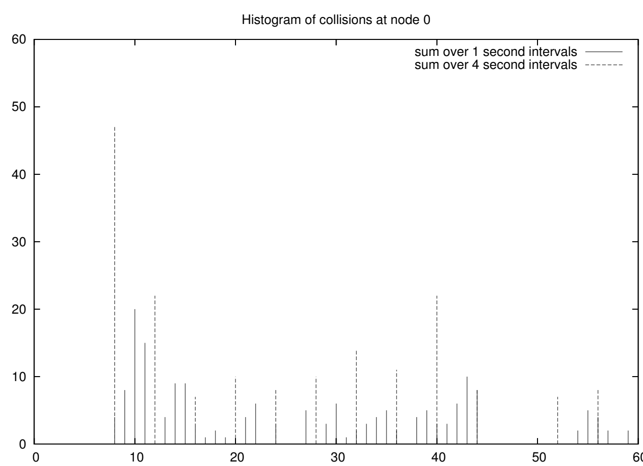

Fig. 8. Collision results with power control

Hence, the use of probabilistic approaches are justified. As shown from the simulation results, the use of SLA improved the system performance in terms of bandwidth and collisions.

Now that the proper power levels have been used to insure less collision levels with the power control, we may apply a different more strict power control algorithms for the DATA packets and have a hybrid power control algorithms separating the transmission power levels for the handshaking and the DATA packets.

References

[1] D.B. Johnson and D.A. Maltz, "Protocols for Adaptive Wireless and Mobile Networks Networking," *IEEE Personal Communications*, pp. 34–42, Feb. 1996.

[2] M.B. Pursley, H.B. Russell, and J.S. Wysocarski, "Energy-Efficient Transmission and Routing Protocols for Wireless Multiple-hop Networks and Spread-Spectrum Radios," in *EUROCOMM*, 2000, pp. 1–5.

[3] S. Narayanaswamy, V. Kawadia, R.S. Sreenivas, and P.R. Kumar, "Power Control in Ad-Hoc Networks: Theory, Architecture, Algorithm and Implementation of COMPOW Protocol," in *European Wireless Conference*, 2002.

[4] V. Kawadia and P.R. Kumar, "Power control and Clustering in Ad Hoc Networks," in *INFOCOM*, 2003.

[5] S. Agarwal, S. Krishnamurthy, R.H. Katz, and S.K. Dao, "Distributed Power Control in Ad-doc Wireless Networks," in *PIMRC01*, 2001.

[6] T.J. Kwon and M.Gerla, "Clustering with Power Control," *IEEE MILCOM*, vol. 2, pp. 1424–1428, November 1999.

[7] M. L. Tsetlin, "On The Bahavior of Finite Automata in Random Media," *Automatic Remote Control*, vol. 22, pp. 1210–1219, 1962.

[8] K.S. Fu and G.J.McMurtry, "A study of stochastic automata as a model for learning and adaptive controllers," *IEEE Transactions on Automatic Control*, vol. 11, pp. 379–387, 1966.

[9] M.A.L. Thathachar and P.S. Sastry, "Varieties of Learning Automata: An Overview," *IEEE Transactions on Systems, Man, and Cybernetics*, vol. 32, no. 6, pp. 711–722, December 2002.

[10] *Learning Automata: Theory and Applications*. New York: Pergamon, 1994.

[11] *Learning Automata and Stochastic Optimization*, ser. Lecture Notes in Control and Information Sciences 225. Springer, 1997.

[12] "NS Simulator," http://www.isi.edu/nsnam/ns/, 2.27.

[13] "IEEE standard for Wireless LAN:Medium Access Control and Physical Layer Specification," P802.11, November 1997.

[14] D. Johnson and D. Maltz, *Dynamic Source Routing in Ad Hoc Wireless Networks*, ser. Mobile Computing. Kluwer Academic Publishers, 1996, ch. 5, pp. 153–181.

[15] T. Chen and M. Gerla, "Global State Routing: A New Routing Scheme for Ad Hoc Wireless Networks," in *Proceedings of IEEE International Conference on Communications*, 1998, pp. 171–175.

[16] J. Broch, D. Maltz, D. Johnson, Y.-C Hu, and J. Jetcheva, "A Performance and Comparision of Multi-Hop Wireless Ad Hoc Network Routing Protocols," in *Proceedings of 4th Annual ACM/IEEE International Conference on Mobile Computing and Networking (Mobicom '98)*, Oct. 1998, pp. 85–97.

[17] C.E. Perkins and P. Bhagwat, "Highly Dynamic Destination-Sequenced Distance-Vector Routing (DSDV) for Mobile Computers," in *Proceedings of the SIGCOMM '94 Conference on Communications Architectures, Protocols and Applications*. ACM, Aug 1994, pp. 234–244.

[18] C.E. Perkins, "Ad-hoc on-demand distance vector routing," in MILCOM '97 panel on Ad Hoc Networks, Nov. 1997.

[19] C.E. Perkins and P. Bhagwat, "Highly Dynamic Desitination-Sequenced Distance-Vector Routing (DSDV) for Mobile Computers," in *ACM SIGCOMM*, vol. 24, 1994, pp. 234–244.