Using Directional Antennas to Increase the Performance of Data Broadcasting Systems in Environments with Locality of Demand

Petros Nicopolitidis [1], Georgios.I.Papadimitriou [2], *Senior Member IEEE*, and Andreas S.Pomportsis [3], *Member, IEEE*

***Abstract*—This paper proposes the use of multiple directional antennas to increase the performance of an adaptive wireless push system in environments characterized by locality of client demands. Simulation results reveal that using up to three antennas suffices for a significant performance increase over the single antenna adaptive wireless push system.**

***Keywords*— Adaptive Data Broadcasting, Directional Antennas, Locality of Demand.**

I. Introduction

Data broadcasting, which has emerged as an efficient way of information dissemination in wireless networks [1], can be characterized by locality of client demands. An example is the case of a traffic information system. Such an application is characterized by locality of demand, as a driver is obviously more interested in information regarding her neighboring streets than for information regarding streets further away.

This paper proposes use of multiple directional antennas to increase the performance of an adaptive push system [2] in environments with locality of demand. Each antenna is equipped with a Learning Automaton whose probability distribution determines the popularity of each information item in the service area of the antenna. Simulation results show significant performance increase over the single-antenna push system can be obtained by using up to three antennas.

The remainder of this paper is organized as follows: Section II presents the proposed multiple antenna adaptive wireless push system. Simulation results which show the performance increase of the proposed approach against the single-antenna push system are presented in Section III. Finally, Section IV summarizes and concludes the paper.

[1] P.Nicopolitidis is with the Department of Informatics, Aristotle University of Thessaloniki, Thessaloniki, Greece (phone: +30-2310-998538, e-mail: petros@csd.auth.gr).

[2] G.I.Papadimitriou is with the Department of Informatics, Aristotle University of Thessaloniki, Thessaloniki, Greece (phone: +30-2310-998221, e-mail: gp@csd.auth.gr).

[3] A.S.Pomportsis is with the Department of Informatics, Aristotle University of Thessaloniki, Thessaloniki, Greece (phone: +30-2310-998045, e-mail: apombo@csd.auth.gr).

II. The Multiple Antenna Adaptive Wireless Push System

A. The Adaptive Wireless Push System

Learning Automata [3, 4, 5] are structures that can acquire knowledge regarding the behavior of the environment in which they operate. In the area of data networking Learning Automata have been applied to several problems, including the design of self-adaptive MAC protocols [6, 7, 8, 9].

In the adaptive wireless push system [2], which enhanced the non-adaptive one of [10], the server is equipped with an S-model Learning Automaton that contains the server's estimate p_i of the demand probability d_i for each data item i among the set of the items the server broadcasts. The estimation probability vector p stores the server's estimation of the actual demand probability vector d that contains the actual choice probabilities of the various information items averaged over the entire client population. Clearly, $\sum_{i=1}^{N} p_i = \sum_{i=1}^{N} d_i = 1$, where N is the number of items in the server's database. At each cycle, the server selects to transmit the item i that maximizes the cost function, $G(i) = (T - R(i))^2 \frac{p_i}{l_i}\left(\frac{1+E(l_i)}{1-E(l_i)}\right)$, where T is the current time, R(i) the time when item i was last broadcast, l_i is the length of item i and $E(l_i)$ is the probability that an item of length l_i is erroneously received. For items that haven't been previously broadcast, R is initialized to -1. If the maximum value of $G(i)$ is shared by more than one item, the algorithm selects one of them arbitrarily. Upon the broadcast of item i at time T, $R(i)$ is changed so that $R(i)=T$.

After the transmission of item i the broadcast server awaits for an acknowledging pulse from every client that was waiting item i. The aggregate received pulse power is used at the server to update the Automaton. For the next broadcast, the server chooses which item to transmit by using the updated vector p.

When the transmission of an item i does not satisfy any waiting client, the probabilities of the items do not change. However, following a transmission that satisfies clients,

the probability of item i is increased. The following Liner Reward-Inaction (L_{R-I}) probability updating scheme [3] is employed after the transmission of item i (assuming it is the server's k^{th} transmission.

$$p_j(k+1) = p_j(k) - L(1-b(k))(p_j(k)-a), \ \forall j \neq i$$
$$p_i(k+1) = p_i(k) + L(1-b(k))\sum_{i \neq j}(p_j(k)-a) \quad (1)$$

where $p_i(k)$ takes values in $(a,1)$ and L,a take values in (0,1). The role of parameter α, is to prevent the probabilities of non-popular items from taking values very close to zero in order to increase the adaptivity of the automaton. This is because if the probability estimate p_i of a item i approaches zero then $G(i)$ will take a value be very close to zero. However, item i, even if unpopular, still needs to be transmitted since some clients may request it. Furthermore, the dynamic nature of client demands might make this item popular in the future. $b(k)$ is the environmental response and is represented by the sum of the received feedback pulses after the server's k^{th} transmission. After normalization the value of $b(k)$ lies in the interval [0,1]. It has been shown in [2] that using the above re-enforcement scheme, the item probabilities estimated by the Automaton converge to the actual demand probabilities for each information item.

The normalization procedure in the calculation of $b(k)$ suggests the existence of a procedure to enable the server to possess an estimate of the number of clients under its coverage. This is made possible by broadcasting a control packet that forces every client to respond with a power-controlled feedback pulse. The broadcast server will use the aggregate received pulse S to estimate the number of clients under its coverage. Thus, upon reception of an aggregate feedback pulse of power Z after the server's k^{th} broadcast, $b(k)$ is calculated as Z/S. This estimation process will take place at regular time intervals with the negligible overhead of broadcasting a unit-length item.

However, as the signal strength of each client's pulse at the server suffers a $1/d^n$ type path loss (with a typical n=4 [11]), the feedback pulses of clients must be power controlled. To this end, every information item will be broadcast including information regarding the signal strength used for its transmission and acknowledging clients set the power of their feedback pulse to be the inverse of the ratio (signal strength of the received item) / (signal strength of the item transmission). Using this form of power control, the contribution of each client's feedback pulse at the server will be the same regardless of the client's distance from the antenna.

A. The Multiple Antenna Server

To the authors' knowledge, locality of demand has not been taken into account in related research so far; on the contrary, clients are assumed to be uniformly distributed inside the service area and generally make item requests using the same or similar patterns (e.g. [2, 10]). In cases however with locality of demand, there exist several client groups at different places with the clients of each group having similar demands, different from those of clients at other groups. When serving these groups via the same server system the difference among group interests reduces overall demand skewness, which in turn reduces overall performance. To alleviate this problem we propose a system that utilizes more than one broadcast servers, each one equipped with a directional antenna and a Learning Automaton for estimation of the demand for information items under the coverage of the respective antenna. This partitions the service area to regions with higher demand skewness and thus results to higher overall performance than the single-antenna system. Higher performance is confirmed by the simulation results in the next Section. Furthermore, simulation reveals that partitioning of the service area to a large number of sectors is not necessary as performance gains are not proportional to the number of sectors. Rather, using up to three servers with directional antennas suffices to exploit the higher demand skewness per antenna service area in order to have significant performance increase over the single antenna push system.

III. Performance Evaluation

We consider broadcast servers having replicas of the same database of *Dbs* equally-sized items. The servers are initially unaware of the demand for each item, so initially every item has a probability estimate p_i of $1/Dbs$. Client demands are a-priori unknown to the servers and location dependent. Item broadcasts are subject to reception errors, with unrecoverable errors per-instance of an information item occurring according to a Poisson process with rate λ, as in [10]. As far as directional antenna service areas are concerned, these are of the same size.

We consider *ClNum* clients that have no cache memory, an assumption also made in other similar research (e.g. [2, 10]). Clients are grouped into G groups each one located at a different geographical region. The placement of groups in the entire service area is made in a uniform manner. Any client belonging to group g, $1 \leq g \leq G$, is interested in the same subset Sec_g of the server's database. All items outside this subset have a zero demand probability at the client. Finally, there do not exist common demands for items between any two clients belonging to different groups.

Assume that such a subset comprises *Num* items. The demand probability d_i for each item in place i in that subset is computed according to the Zipf distribution, which is used in other papers dealing with research data broadcasting as well ([2, 10, 12]): $d(i) = c\left(\frac{1}{i}\right)^{\theta}$ where $c = 1/\sum_k \left(\frac{1}{k}\right)^{\theta}$, $k \in [1..Num]$. The data access skew coefficient θ is a parameter that when increased, increases

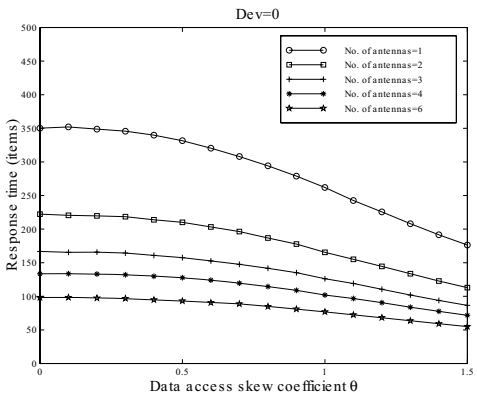

Fig.1: Overall response time versus data access skew coefficient θ for *Dev*=0. Group size skew coefficient $\theta 1$=0.

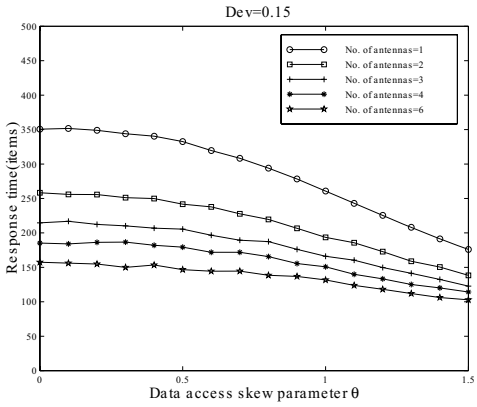

Fig.2: Overall response time versus data access skew coefficient θ for *Dev*=0.15. Group size skew coefficient $\theta 1$=0.

demand skewness.

To simulate some "noise" in client locations, we introduce parameter *Dev*, which determines the percentage of clients that deviate from initial client placement. Such clients' positions are changed towards another group selected in a uniform manner from the set of remaining groups. In order to model different group sizes, we also calculated the size of each group *g* via the above-mentioned Zipf distribution, governed by the group size skew coefficient $\theta 1$.

The simulation is ended when *N* broadcasts have been made by each antenna. Finally, the overhead due to the duration of the feedback pulse and the signal propagation delay is considered to be very small compared to the item transmission time (parameter *Ovh*), as would happen in low-speed broadcasting applications spanning an area of several kilometers.

The following parameters were used for all experiments: path loss exponent *n*=4, *Dbs*=600, *ClNum*=10000, *G*=12, Sec1=[1..120], Sec2=[121..210], Sec3=[211..270], Sec4=[271..330], Sec5=[331..390], Sec6=[391..420], Sec7=[421..450], Sec8=[451..480], Sec9=[481..510], Sec10=[511..540], Sec11=[541..570], Sec12=[571..600], *N*=100000, *Ovh*=0.001, $a=10^{-4}$, *L*=0.15, λ=0.1.

Figures 1-3 contain results that compare the overall response time (overall mean access time among the

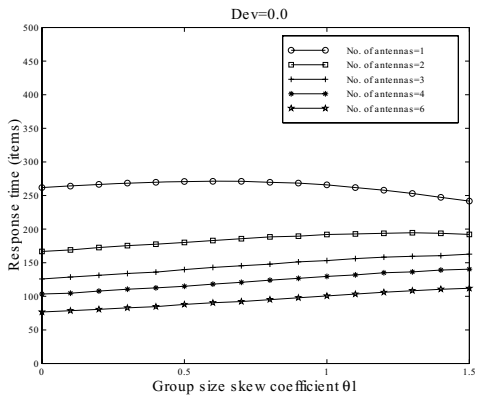

Fig. 3: Overall response time versus group size skew coefficient $\theta 1$ for *Dev*=0. Data access skew coefficient θ=1.

clients) of the multi-antenna systems to that of the single antenna one. The main conclusions that are drawn from the Figures are:

- The performances of all schemes improve for increasing values of the data skew parameter θ (Figures 1 and 2). This is expected behavior when demand skewness increases and this knowledge is made available to the broadcast server either a-priori (e.g. [10]) or dynamically (e.g. [2]).
- The performances of multiple antenna systems are superior to that of the single antenna one in all cases. This is due to the fact that in the multi-antenna cases, the Automaton at each antenna deals with demands of clients only at the respective service area. Combined with the locality of demand (different groups demand different database subsets) inside each antenna service area, this results to increased demand skewness compared to the overall skewness and thus raises overall performance.
- Using more than three antennas does not significantly increase performance. Therefore, a small number of antennas suffices for a significant performance increase.
- When some clients have broken away from their main group (Figure 2, *Dev*>0) and are located elsewhere, the performance gains of multi-antenna systems decline, remaining however significantly superior to that of the single antenna system. This is because as not all members of a group are located at the same service area, in some cases antennas will receive acknowledgments (and thus raise the demand estimate) for items not demanded by the main groups under their coverage. This reduces item demand skewness inside their service areas with an accompanying decrease in the performance gain of the multi-antenna systems.
- The performances of the multiple antenna systems are superior to that of the single antenna one when varying group sizes (Figure 3). The slight performance decrease for high values of $\theta 1$ for the multiple antenna systems is due to the fact that in these experiments clients belonging to the first group access a larger database subset, a fact that makes the demand skew and thus performance for this group less than that of the other groups. As $\theta 1$ increases, the size of the first group

also increases and its reduced performance increasingly affects overall performance.

IV. CONCLUSION

This paper proposes use of multiple directional antennas to increase the performance of an adaptive wireless push system in environments with locality of demand. Each antenna is equipped with a Learning Automaton whose probability distribution determines the popularity of each information item in the service area of the antenna. Simulation results reveal that using up to three antennas suffices for a significant performance increase over the single antenna adaptive wireless push system.

REFERENCES

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

[2] P.Nicopolitidis, G.I.Papadimitriou and A.S.Pomportsis, "Using Learning Automata for Adaptive Push-Based Data Broadcasting in Asymmetric Wireless Environments", *IEEE Transactions on Vehicular Technology*, Vol.51, No.6, pp. 1652-1660, November 2002.

[3] K.S.Narendra; M.A.L.Thathachar, "Learning Automata: An Introduction", Prentice Hall, 1989.

[4] G.I.Papadimitriou, "A New Approach to the Design of Reinforcement Schemes for Learning Automata: Stochastic Estimator Learning Algorithms", *IEEE Transactions on Knowledge and Data Engineering*, Vol.6, No.4, pp. 649-654, August 1994.

[5] G.I.Papadimitriou, "Hierarchical Discretized Pursuit Nonlinear Learning Automata with Rapid Convergence and High Accuracy", *IEEE Transactions on Knowledge and Data Engineering*, Vol.6, No.4, pp.654-659, August 1994.

[6] G.I.Papadimitriou and A.S Pomportsis, "Learning Automata-Based TDMA protocols for Broadcast Communication Systems with Bursty Traffic*", IEEE Communication Letters*, Vol.4, No.3, pp.107-109, March 2000.

[7] G.I.Papadimitriou and A.S.Pomportsis, "Self-Adaptive TDMA Protocols for WDM Star Networks: A Learning-Automata-Based Approach", *IEEE Photonics Technology Letters*, Vol.11, No.10, pp. 1322-1324, October 1999.

[8] G.I.Papadimitriou and D.G.Maritsas, "Learning Automata-Based Receiver Conflict Avoidance Algorithms for WDM Broadcast-and-Select Star Networks", *IEEE/ACM Transactions on Networking*, Vol.4, No.3, pp.407-412, June 1996.

[9] 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, pp.453-463, March 2003.

[10] N.H.Vaidya, S.Hameed, "Scheduling Data Broadcast In Asymmetric Communication Environments", *Wireless Networks*, Vol.5, No.3, pp.171-182.

[11] B.Andersen, T.S.Rappaport and S.Yoshida, "Propagation Measurements and Models for Wireless Communication Channels", *IEEE Communications Magazine*, Vol.33, No.1, pp.42-49, January 1995.

[12] S.Acharya, M.Franklin and S.Zdonik, "Dissemination-based Data Delivery Using Broadcast Disks", *IEEE Personal Communications*, Vol.2, No.6, pp. 50-60, December 1995.