Multiple-Antenna Data Broadcasting for Environments With Locality of Demand

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***Abstract*—Data broadcasting is an efficient way of delivering data to mobile clients having a high degree of commonality in their demand patterns. This paper proposes the use of multiple directional antennas to increase the performance of an adaptive wireless push system in environments that are characterized by the 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.**

***Index Terms*—Adaptive data broadcasting, directional antennas, locality of demand.**

I. Introduction

Data broadcasting has emerged as an efficient way of information dissemination in asymmetric wireless networks [1], where client needs for data items are usually overlapping. In such cases, broadcasting stands to be an efficient solution since the broadcast of a single data item is likely to satisfy a (possibly large) number of clients. Communications asymmetry, which can prohibit clients from efficiently submitting actual requests to the server, is due to a number of facts, such as asymmetry in equipment (e.g., lack of client transmission capability and client power limitations), asymmetry in the network system (e.g., small uplink/downlink bandwidth ratio), and application asymmetry (e.g., traffic pattern of client–server applications). Furthermore, certain applications 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 information regarding streets further away.

This paper proposes the 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 reveal that 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 discusses related research in the area of wireless push systems. Section III 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 IV. Finally, Section V summarizes and concludes this paper.

II. Related Research

The first work in the area of wireless push systems used the flat approach [3], which schedules all items with the same frequency. However, it has been shown that in order to minimize the overall mean access time (referred to hereinafter as response time) among the client population, broadcast schedules must be periodic [4] and should be constructed in such a way that the variance of spacing between consecutive instances of the same item is reduced [5].

An approach that satisfied the preceding two constraints was proposed in [6] and is known as the Broadcast Disks model. This model proposed a method of coplacing multiple disks spinning at different frequencies on a single broadcast channel. The most frequently demanded data are placed on the faster disks. Thus, periodic schedules are produced, with the most popular data being broadcast more frequently. This work was enhanced later by dealing with the impact of changes at the values of the data items [7] and the addition of an uplink channel through which clients can send requests to the server [8].

A drawback of Broadcast Disks is the fact that it is constrained to fixed-sized data items and does not present a way of determining neither the optimal number of disks to use nor their relative frequencies. Those numbers are selected empirically, and as a result, the server may not broadcast data items with optimal frequencies, even in cases of static and *a priori* known client demands. Furthermore, the rigid enforcement of the constraint for minimization of the variance of spacing between consecutive instances of the same item leads to schedules where instances of the same item are equally spaced. This fact can lead to schedules that possibly include empty and, thus, unused periods (holes). Finally, the Broadcast Disks approach is not adaptive to dynamic client demands since it is based on the server's *a priori* knowledge of static client demands, resulting in predetermined broadcast schedules.

An interesting paper that builds on the method of Broadcast Disks is [9]. It tries to satisfy client requests in a low time while, at the same time, achieving low-energy consumption by the client. This method can achieve the following: 1) determine a way to assign the data items to be broadcast to the various disks so that overall response time is reduced; 2) determine the number of disks to use; and 3) use indexing in order to provide energy efficiency.

Push-based systems are also proposed in [10]. This method also produces periodic schedules, as stated in [11]. According to it, the construction of the broadcast when all users are tuned to the same channel is based on the following two arguments: 1) Broadcast schedules with minimum response time are produced when the intervals between successive instances of the same item are equal [5]. 2) Under the assumption of equally spaced instances of the same items, the minimum response time occurs when the server broadcasts an item i, with the spacing between consecutive instances of i being proportional to the factor $\sqrt{l_i/d_i}$, where d_i is the demand probability for item i, and l_i is the item's length.

Based on the arguments presented previously, Vaidya and Hameed [10] proposes a scheduling algorithm that tries to equalize the space between successive instances of the same item i. According to the algorithm, the broadcast scheduler selects to broadcast item i having the largest value of cost function G, i.e.,

$$G(i) = (T - R(i))^2 \frac{d_i}{l_i} \left(\frac{1 + E(l_i)}{1 - E(l_i)} \right), \qquad 1 \leq i \leq M \quad (1)$$

where T is the current time, $R(i)$ is the time when item i was last broadcast, l_i is the length of item i, $E(l_i)$ is the probability that an item of length l_i is erroneously received, and M is the number of items in the server's database. For items that have not been previously broadcast, $R(i)$ is initialized to -1, and if the maximum value of $G(i)$ is given by more than one item, the algorithm selects one of them

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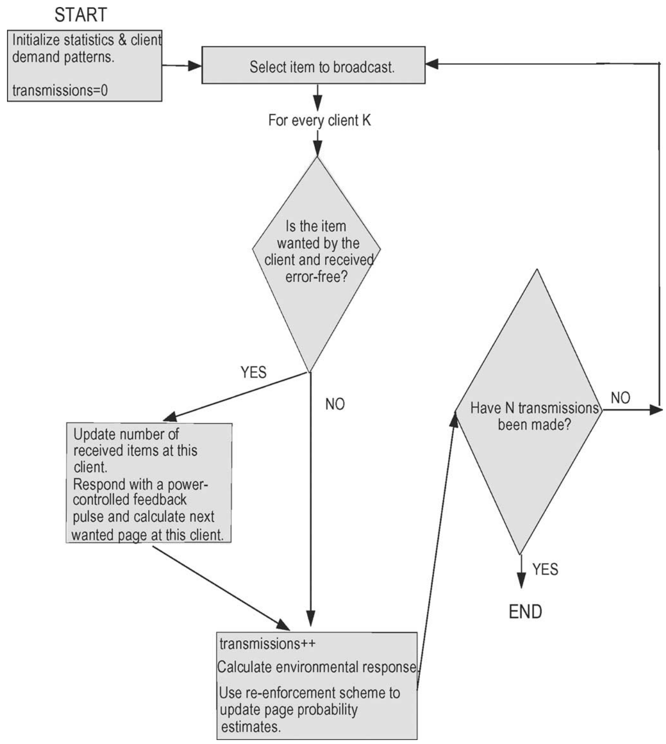

Fig. 1. Diagram of the simulation process for each sector.

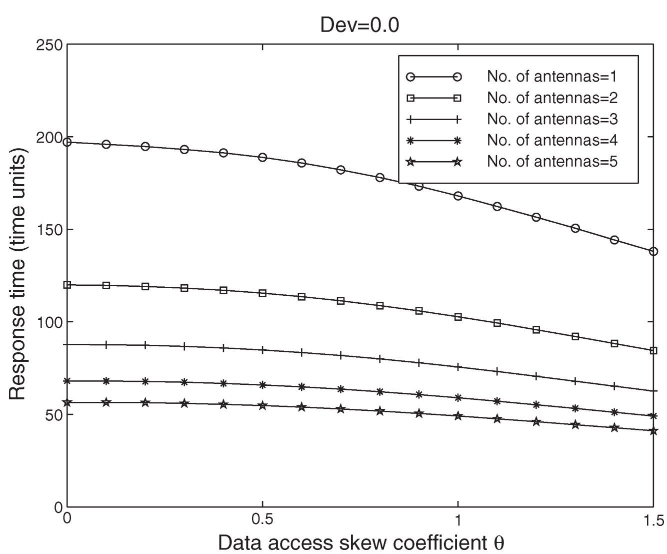

Fig. 2. Response time versus data access skew coefficient θ for $Dev = 0.0$ and 20 groups. Group size skew coefficient $\theta 1 = 0.0$.

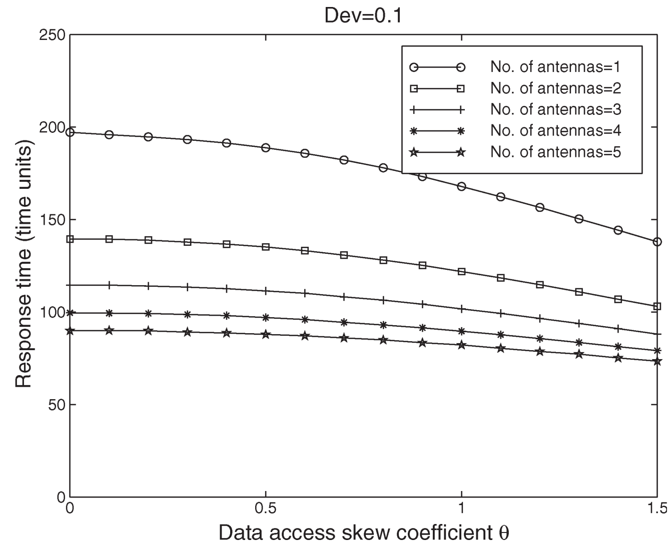

Fig. 3. Response time versus data access skew coefficient θ for $Dev = 0.1$ and 20 groups. Group size skew coefficient $\theta 1 = 0.0$.

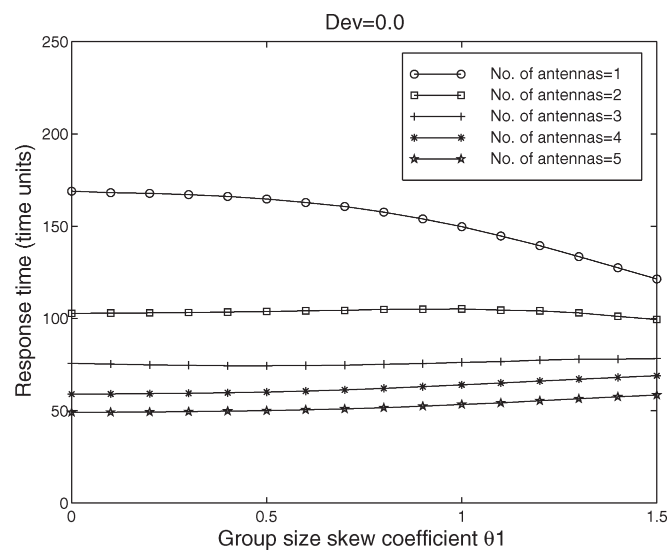

Fig. 4. Response time versus group size skew coefficient $\theta 1$ for $Dev = 0.0$ and 20 groups. Data access skew coefficient $\theta = 1.0$.

arbitrarily. Upon the broadcast of item i at time T, $R(i)$ is changed so that $R(i) = T$.

As stated by its authors, in contrast to [6], the method in [10] has the advantage of automatically using the optimal frequencies for item broadcasts. Furthermore, the constraint of equally spaced instances of the same item is not rigidly enforced—a fact that leads to elimination of empty periods in the broadcast. Finally, [10] works with items of different sizes as well. This assumption is obviously more realistic compared to that of fixed-length items that are made in the Broadcast Disks approach. However, the main drawback of the method in [10] remains to be its lack of adaptivity and, therefore, its inefficiency in environments with dynamic client demands.

The method in [2] proposes a push-based system that is adaptive to dynamic client demands. The system uses a learning automaton at the broadcast server in order to provide adaptivity in environments with dynamic and *a priori* unknown client demands while maintaining its computational complexity. Using a simple feedback from the clients, the automaton continuously adapts to the overall client population demands in order to reflect the overall popularity of each data item. It is shown in [2] that, contrary to the nonadaptive method of [10], the adaptive system provides superior performance in an environment where client demands change over time, with the nature of these changes being unknown to the broadcast server.

III. Multiple-Antenna Adaptive Wireless Push System

A. *Adaptive Wireless Push System*

Learning automata [12]–[14] are structures that can acquire knowledge regarding the behavior of the environment in which they operate.

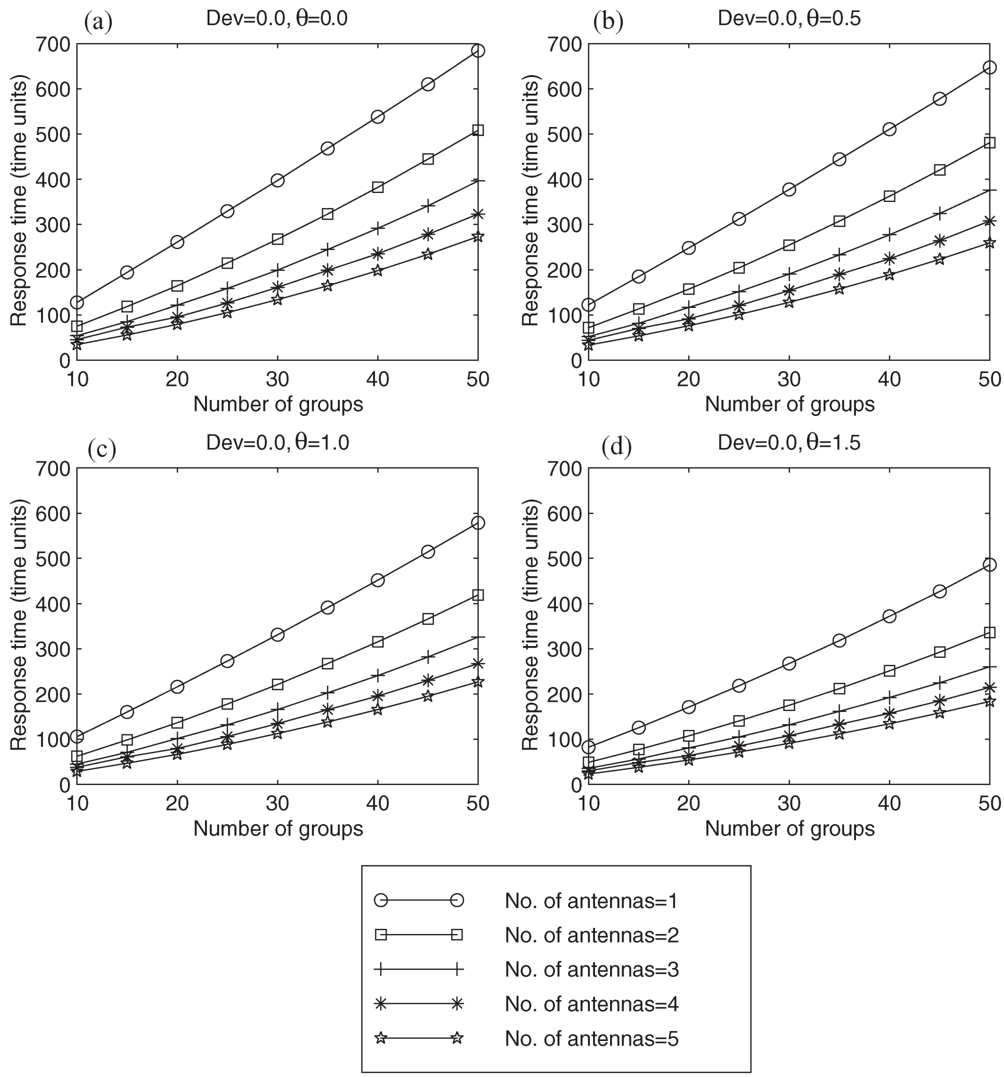

Fig. 5. Response time versus the number of groups for various values of θ and $Dev = 0.0$. Group size skew coefficient $\theta 1 = 0.0$. Each group always accesses the same number of items.

In the area of data networking, learning automata have been applied to several problems, including the design of self-adaptive medium-access control protocols [15]–[18].

In the adaptive wireless push system [2], which enhanced the nonadaptive one of [10], the server is equipped with an S-model learning automaton that contains the server's estimate p_i of demand probability d_i for each data item i among the set of items that the server broadcasts. Clearly, $\sum_{i=1}^{M} d_i = 1$, where M is the number of items in the server's database.

According to [10], the server selects to broadcast item i having the largest value of cost function $G(i)$ given in (1). The adaptive method of [2] extends this approach: 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. The probability distribution vector p that is maintained by the automaton estimates demand probability d_i (and thus the popularity) of each information item i. 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 Linear Reward–Inaction (L_{R-I}) probability updating scheme [12] is employed after the transmission of item i (assuming it is the server's kth transmission), i.e.,

$$\begin{aligned} p_j(k+1) &= p_j(k) - L(1-b(k))(p_j(k)-a) \qquad \forall j \neq i \\ p_i(k+1) &= p_i(k) + L\,(1-b(k)) \sum_{i \neq j} (p_j(k)-a) \end{aligned} \tag{2}$$

where $p_i(k) \in (a,1)\ \forall k$, and $L, a \in (0,1)$. Parameter a prevents the probabilities of nonpopular items from taking values in the neighborhood of zero and thus increases the adaptivity of the automaton. $b(k)$ is the environmental response and is represented by the sum of the received feedback pulses after the server's kth transmission. After normalization, the value of $b(k)$ is in the interval [0, 1]. It has been shown in [2] that using the preceding reinforcement scheme, the item probabilities estimated by the automaton converge to the actual demand probabilities for each information item.

The normalization procedure needs a mechanism that will enable the server to possess an estimate of the number of clients under its coverage. This is achieved by the broadcasting of a control packet that notifies all clients in the service area of the antenna to respond with a feedback pulse. The server will use this aggregate received pulse to estimate how many clients are within its coverage area. However,

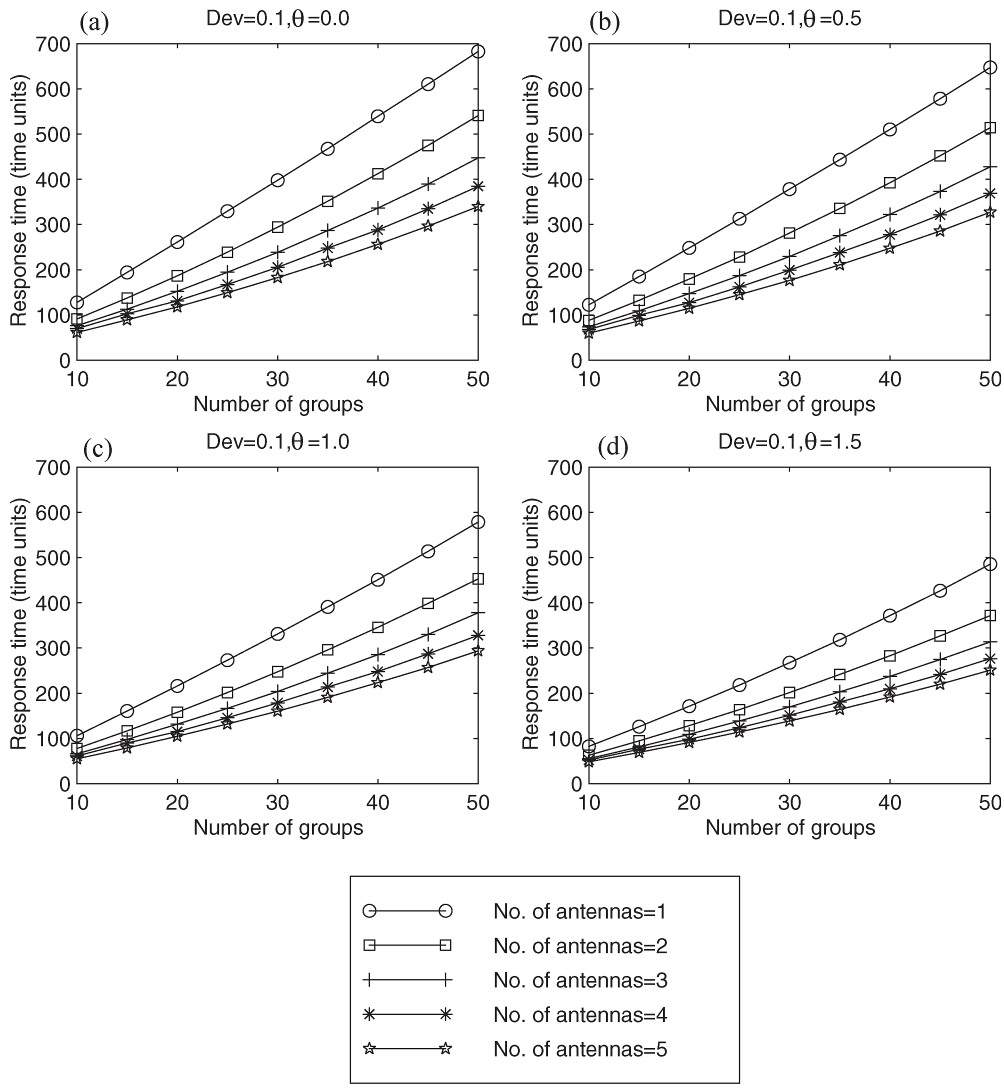

Fig. 6. Response time versus the number of groups for various values of θ and $Dev = 0.1$. Group size skew coefficient $\theta 1 = 0.0$. Each group always accesses the same number of items.

as the signal strength of each client's pulse at the server suffers a $1/d^n$-type path loss (with a typical $n = 4$ [19]), 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. Clients that acknowledge this item will 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.

Estimation of the size of client groups has been addressed again in the literature. For example, in [20], online estimation algorithms for determining the members of a group is proposed. This approach is based on the use of a probabilistic acknowledgement scheme coupled with signal processing techniques and has shown very good performance under the assumptions of Poissonian arrivals of subscribers, with receiver lifetimes being exponential or hyperexponential distributed. In our approach, for the broadcast of each item, the received feedback signals at the server pass through an operational amplifier [21], [22] that integrates the energy received during a time interval t_p after the broadcast of the item. This time interval is equal to the sum of the feedback duration and the maximum round-trip propagation delay (the round-trip delay from the server to a client that is located at the border of the coverage area). From the total energy received during this interval, the server can conclude about how many stations have transmitted a feedback pulse [22], [23]. Then, the operational amplifier is being reset in order to begin a new integration of duration t_p after the broadcast of the next item.

The estimation of clients at regular time intervals means that, between two consecutive estimations, the broadcast server may, for some time, possess imprecise knowledge regarding the number of clients within the cell. Thus, we define that clients arriving at the coverage area of the system are allowed to send feedback for received pages only after they have joined the process for the estimation of the number of clients within the cell. This can be seen as a kind of registration that aims to maintain the precision of the environmental response in cases of an increasing number of clients between consecutive estimations. On the other hand, a decreasing number of clients between consecutive estimations leads to a lower value of $\beta(k)$ and, thus, $L\beta(k)$. This can be seen as a temporary reduction of adaptation parameter L, leading to slower convergence of the automaton. The same holds in the case where the received feedback is "noisy." In such a case, it will obviously

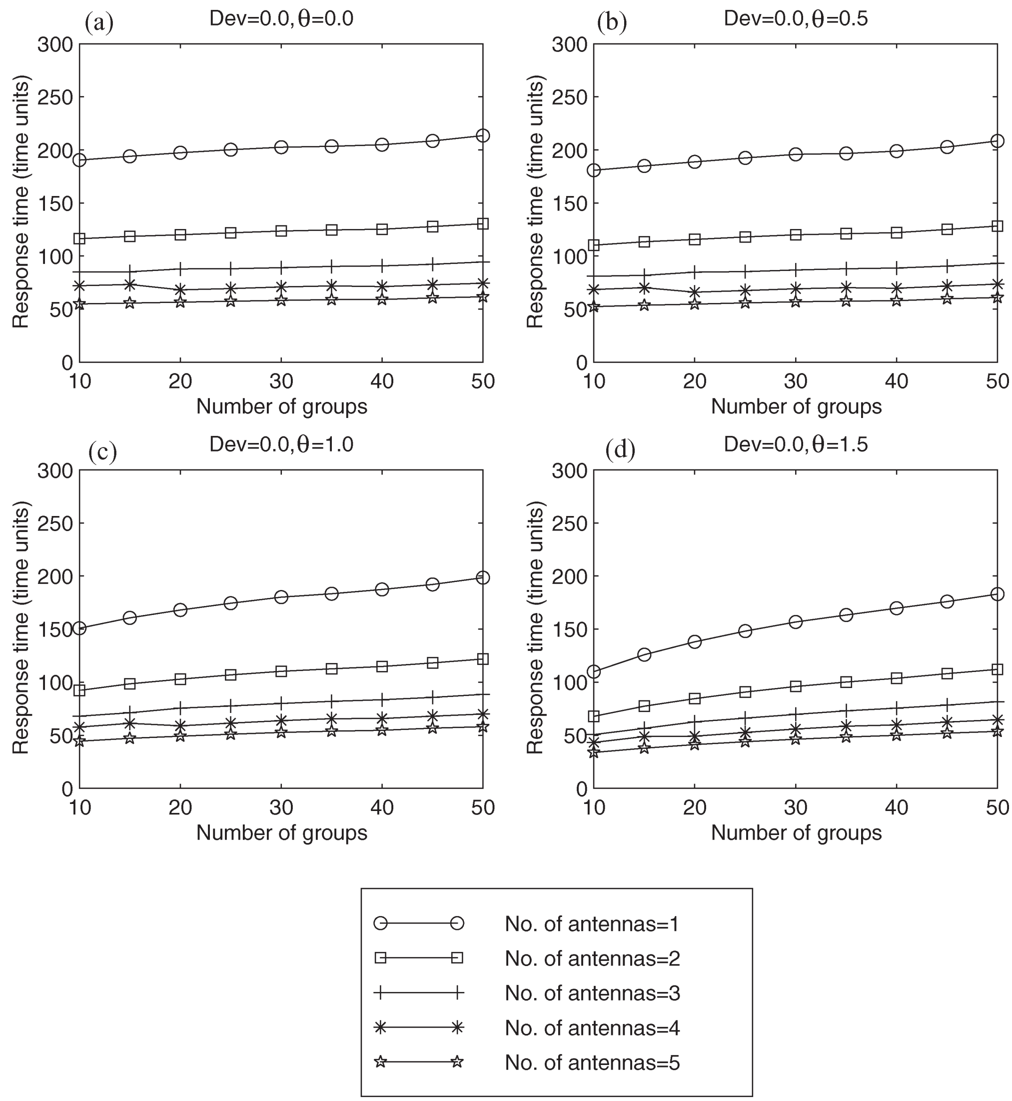

Fig. 7. Response time versus the number of groups for various values of θ and $Dev = 0.0$. Group size skew coefficient $\theta 1 = 0.0$. Each group accesses a subset of the same fixed-size server database. Subsets are of the same size for each group.

be of lower power than in the ideal case, leading again to a lower value of $L\beta(k)$, which can be seen again as a temporary reduction of the adaptation parameter L and, thus, of the convergence speed of the automaton.

B. 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] and [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, which are different from those of the clients at other groups. When serving these groups via the same server system, the difference in 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 server, 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 in 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.

IV. Performance Evaluation

A. Simulation Environment

We performed our experiments with an event-driven simulator coded in C. The simulator models mobile clients, the broadcast server, and the server–client links as separate entities. Fig. 1 shows a diagram describing the simulation process for each antenna. For an K-antenna system, K such processes run in parallel. For each distinct experiment, the simulator is run five times in order to obtain statistically meaningful

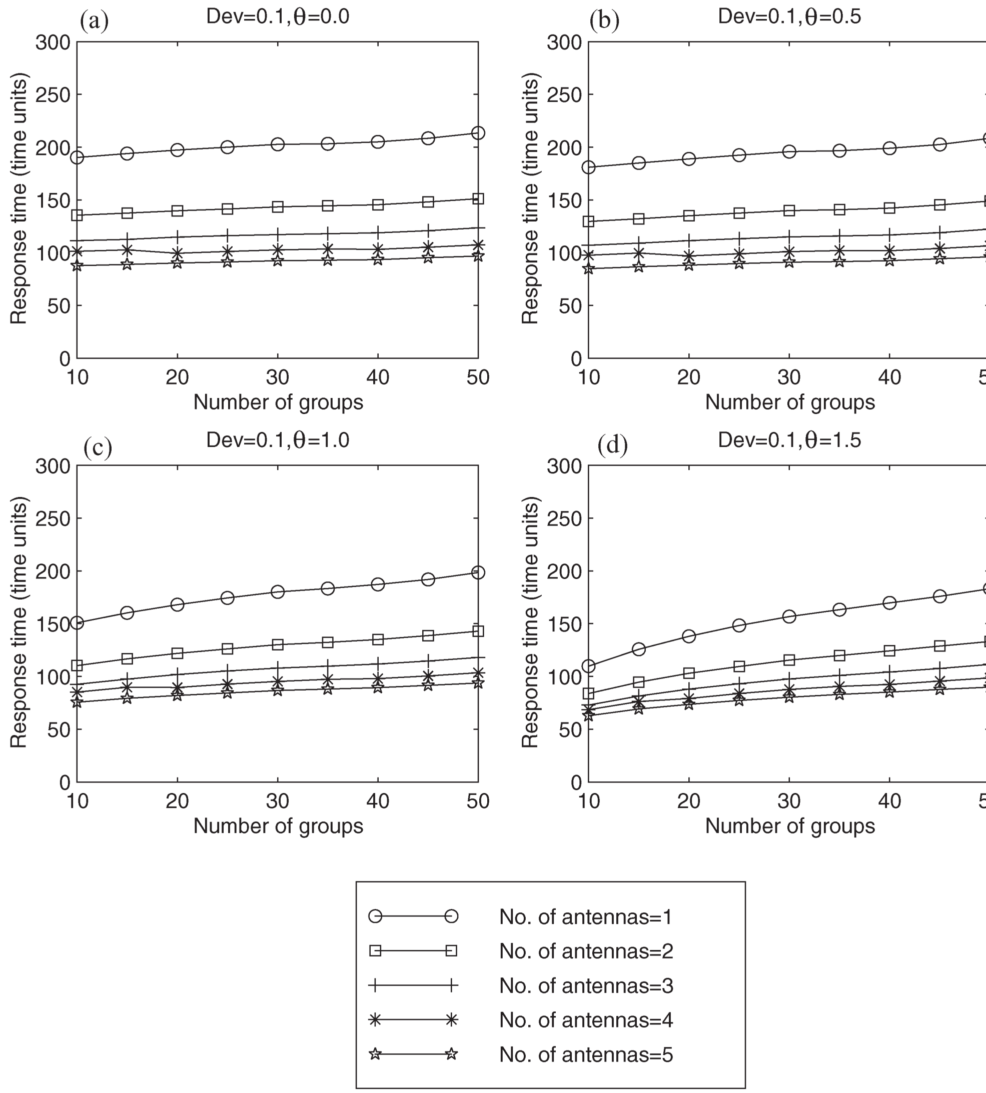

Fig. 8. Response time versus the number of groups for various values of θ and $Dev = 0.1$. Group size skew coefficient $\theta 1 = 0.0$. Each group accesses a subset of the same fixed-size server database. Subsets are the same size for each group.

results and narrow confidence intervals. All the response time results that we have obtained have 95% confidence intervals inside a range of $\pm z$ time units, with $z < 1$. Therefore, the confidence level of the simulation results is high.

We consider broadcast servers having replicas of the same database of Dbs equally sized items. A time unit is equal to the duration of an item broadcast. 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 a page 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. Finally, the power-controlled feedback pulses that arrive at the server after the broadcast of a certain item represent the number of clients that acknowledged the reception of the item.

We consider $ClNum$ clients that have no cache memory—an assumption that is also made in other similar research (e.g., [2] and [10]). To simulate propagation loss, we use a path loss model of $1/x^4$, where x is the distance between the client and the server's antenna. 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.

Assume that such a subset comprises Num pages. The demand probability d_i for each item in place i in that subset is computed according to Zipf distribution, which is used in other papers dealing with data broadcasting as well [2], [6], [10]: $d_i = c(1/i)^\theta$, where $c = 1/\sum_k (1/k)^\theta$, $k \in [1, \ldots, Num]$. The data access skew coefficient θ is a parameter that, when increased, increases demand skewness. A value of $\theta = 0.0$ produces a subset with its items being equiprobably demanded.

To simulate some "noise" in client locations, we introduce parameter Dev, which determines the percentage of clients that deviate from the initial group membership. Such clients' positions are changed toward another group that is 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 aforementioned Zipf distribution, which is governed by the group size skew coefficient $\theta 1$. A value of $\theta 1 = 0.0$ produces equally sized groups.

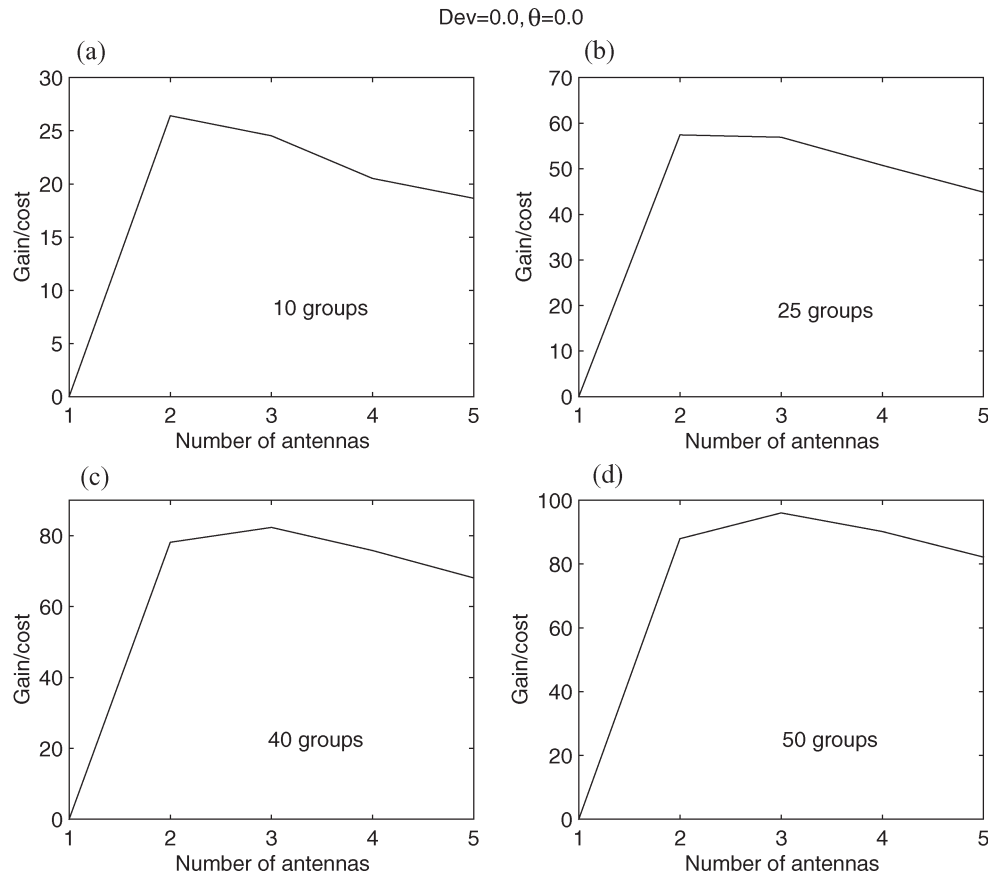

Fig. 9. Ratios of performance gain to antenna costs versus the number of used antennas for $\theta = 0$ and $Dev = 0.0$. Each group always accesses the same number of items.

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 $n = 4, ClNum = 10\,000, N = 10\,000, Ovh = 10^{-3}, L = 0.15, a = 10^{-4}$, and $\lambda = 0.1$.

B. Simulation Results

In this section, we present the results of the simulation experiments that are shown in the figures and we summarize the conclusions that are derived by examining the results in certain figures or limited groups of figures.

Figs. 2 and 3 present results for the system response time (calculated as the overall mean access time) versus the data access skew coefficient θ for $Dev = 0.0$ and $Dev = 0.1$, respectively. In these experiments, we used $Dbs = 300$ and $G = 20$, and we have set different groups to access different subsets of the database that do not overlap. Each such subset comprises 15 pages. Thus, all items in the server database can be demanded by the client population.

Two conclusions can be drawn from the preceding figures.

1) The absolute performances of all schemes improve for increasing values of the data skew parameter θ. This is an 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]).
2) When some clients have broken away from their main group (the case of $Dev > 0$ shown in Fig. 3) and are located elsewhere, the performance gains of multiantenna systems decline, remaining however significantly superior to those of the single-antenna system. This is because, as not all members of a group are located in the same service area, in some cases, antennas will receive acknowledgments (and thus raise the demand estimate) for items that are 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 multiantenna systems.

In Fig. 4, we plot the response time for varying group sizes and $\theta = 1$ for $Dbs = 300$ and $G = 20$. Again, we have set different groups to access different subsets of the database that do not overlap with each such subset comprising 15 items.

Conclusions can be drawn from the preceding figure.

- The performances of the multiple-antenna systems are superior to those of the single-antenna one when varying group sizes.
  - — The performance increase (response time decrease) of the single-antenna system for large values of $\theta 1$ is due to the fact that, in such cases, the vast majority of clients belong to the same group. Thus, the vast majority of the clients make requests for the same database subset. This fact, of course, increases overall demand skewness, which in turn causes the increased performance of the single-antenna system.
  - — The slight performance decrease (response time increase) for high values of $\theta 1$ for the multiple-antenna systems is

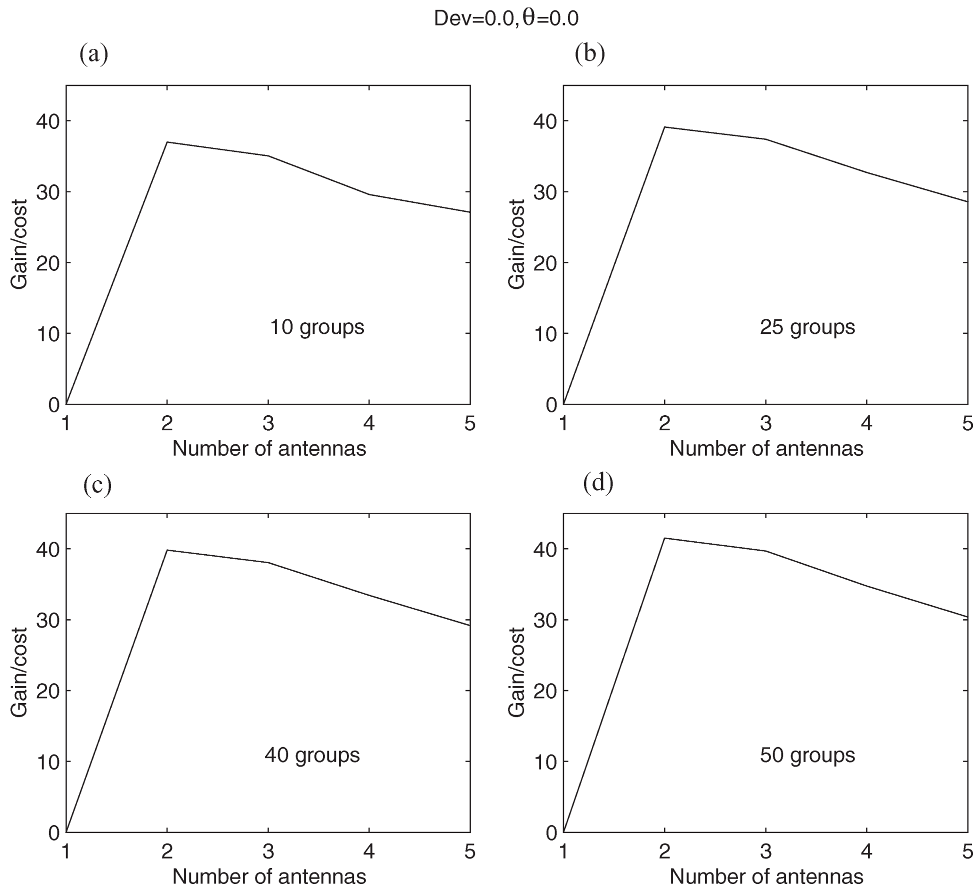

Fig. 10. Ratios of performance gain to antenna costs versus the number of used antennas for $\theta = 0$ and $Dev = 0.0$. Each group accesses a subset of the same fixed-size server database. Subsets are of the same size for each group.

due to the fact that when the number of antennas increases, each antenna serves a decreasing number of groups. Thus, as the number of antennas increases, the client population under the coverage of each antenna makes requests for even smaller database subsets. Apart from the increase in demand skewness that was mentioned previously, this also means that the ratio of demanded items to the number of items in the entire database decreases. However, the server also broadcasts, albeit not seldomly, the remaining items that are not demanded by the clients under the coverage of the antenna. The broadcast of these items results in an increase in the overhead of broadcasting the items that are demanded by the clients under the coverage of each antenna of a multiantenna system. This increased overhead causes the slight performance decrease for high values of $\theta 1$ for the multiple-antenna systems, which is more pronounced for systems with larger number of antennas. We remind here that the automaton at each antenna must store demand estimates and make broadcasts for every item in the server database (and not just for those items in demand) in order to be able to serve clients that are roaming between antennas.

— The performance decrease (response time increase) for high values of $\theta 1$ for a specific multiantenna system is due to the fact that in such cases, the vast majority of clients belong to the same group. Thus, the aforementioned overhead increasingly affects a specific antenna area (that which serves the largest group) with an accompanying negative impact on overall performance. On the other hand, for small values of $\theta 1$, the aforementioned overhead tends to be equally divided among the antennas, thus leading to a slightly better performance.

Figs. 5 and 6 present results for the response time versus the number of groups for various values of θ and for $Dev = 0.0$ and $Dev = 0.1$, respectively. The group size skew coefficient $\theta 1$ is 0.0. Each group always accesses a subset comprising the same number of items, which we set to 20. The subsets that are accessed by any two different groups do not overlap.

A conclusion can be drawn from the preceding figures.

- When the different client groups always access the same number of items, an increase in the number of groups also increases the size of the server database. In such cases, the performances of the multiantenna systems are significantly higher than those of the single-antenna one. The performance decrease (response time increase) of all schemes in these figures for an increasing number of groups is due to the fact that an increase in the number of groups also increases the size of the server database. When all the other parameters remain the same, an increase in the size of the server database also increases the response time at the clients [6], [10].

Figs. 7 and 8 present results for the response time versus the number of groups for various values of θ and for $Dev = 0.0$ and $Dev = 0.1$, respectively. The group size skew coefficient $\theta 1$ is 0.0. In these experiments, groups always access nonoverlapping subsets of equal sizes from a database that has a fixed size $Dbs = 300$.

Conclusions can be drawn from the preceding figures.

- When the size of the server database is always the same, irrespective of the number of client groups, the performances of the multiantenna systems are again significantly higher than those of the single-antenna one.

— We observe a slight performance decrease (response time increase) for an increasing number of groups for $\theta = 0$. This is due to the fact that, as the number of groups increases, the use of a fixed database size makes each group demand items from a subset of decreasing size. The smaller these subsets are, the more time is spent by a client waiting to receive an item. For example, for the trivial case of a single group that accesses the entire server database, each client will wait in the average half the duration of the flat broadcast schedule [6] (which is produced due to the fact that all items are equiprobable as $\theta = 0.0$). On the other hand, when each group of clients always accesses a single item that is different than that demanded by other groups, its waiting time will be equal to the duration of the flat broadcast schedule.

— For larger values of θ, the performances for an increasing number of groups decrease more. Apart from the preceding remark, this is attributed to the following fact as well, when $\theta > 0$: As mentioned previously, for an increasing number of groups, the server database is partitioned in a larger number of subsets that are demanded by the client groups. This causes the ratio of "hot" items to the same database size to increase. This translates into decreased overall skewness of demands, which causes the additional performance decrease (response time increase).

Fig. 9 shows the ratio of performance gain to the antenna costs of a multiantenna system versus the number of used antennas for the case of Fig. 5(a) (thus, for $\theta = 0$ and $Dev = 0.0$) for 10, 25, 40, and 50 groups. Fig. 10 shows the ratio of performance gain to the antenna costs of a multiantenna system versus the number of used antennas for the case of Fig. 7(a) (thus, for $\theta = 0$ and $Dev = 0.0$) for 10, 25, 40, and 50 groups.

A conclusion can be drawn from the preceding figures.

- The performance gain of a multiantenna system compared to the single-antenna one does not always justify the number of antennas that it uses. It can be seen from Figs. 9 and 10 that the optimal number of antennas is up to three since a larger number of antennas leads to a lower number for this ratio. Thus, using more than three antennas does not result in performance gains that justify their use. Therefore, using up to three antennas suffices for a significant performance increase. We have obtained similar results for Figs. 5(b)–(d), 6(a)–(d), 7(b)–(d), and 8(a)–(d) as well.

Fig. 11 shows results for the response time versus the data access skew coefficient θ for the case where there exists a 50% overlapping between the subsets that are accessed by any two groups i and $i+1$. In this figure, $Dev = 0.0, \theta 1 = 0, G = 20$ groups, and $Dbs = 300$.

A conclusion can be drawn from the preceding figure.

- The performances of the multiple-antenna systems remain higher than those of the single-antenna one in cases where there exists overlapping between the subsets that are accessed by any two groups i and $i+1$. This is due to the fact that the automaton at each antenna deals just with the demands of clients in the respective antenna area and is not affected by the operation of the automatons in the other antennas. Thus, what a certain automaton always sees, regardless of the existence of overlapping or not, is just a probability distribution of the demands that were made by the clients under the service area of the respective antenna.

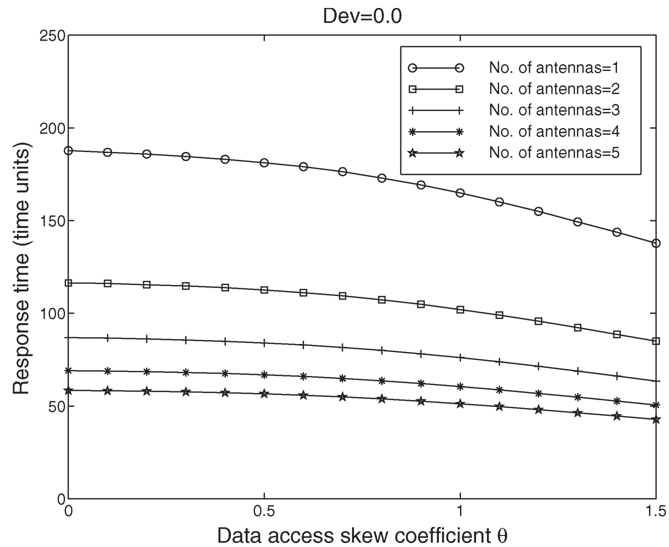

Fig. 11. Response time versus data access skew coefficient θ for $Dev = 0.1$ and 20 groups. Group size skew coefficient $\theta 1 = 0.0$. Group demands overlap.

Finally, a more generic conclusion that stems from many of the figures previously discussed is the fact that the performances of multiple-antenna systems are superior to those of the single-antenna one in all cases. This is due to the fact that, in the multiantenna cases, the automaton at each antenna deals with the demands of clients that are 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 in increased demand skewness compared to the overall skewness and thus raises overall performance.

V. Conclusion

This paper proposes the 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.

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Simple Tight Upper Bounds for Average SEP and BEP of Coherent Diversity M-ary Biorthogonal Signals Over Fading Channels

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***Abstract*—This paper presents simple tight upper bound expressions for the average symbol error probability and bit error probability of coherent M-ary biorthogonal signals over fading channels with diversity reception. The upper bounds, which do not involve numerical integration and are expressed with only elementary functions, can be efficiently evaluated. In addition, they are valid for different diversity-combining techniques, as well as for arbitrarily correlated and/or nonidentically distributed channels. The tightness of the derived upper bounds is clarified under various channel conditions. Numerical results are also provided to demonstrate the impact of nonidentical channels on the system average error performance.**

***Index Terms*—Average error performance, biorthogonal signals, diversity reception, fading channels.**

I. Introduction

The biorthogonal signal set is a special case of N-orthogonal signal sets when $N = 2$ [1], [2, Ch. 4]. For a biorthogonal signal set of size M (usually referred to as M-ary biorthogonal signals), the modulated signals can be partitioned into $M/2$ disjoint equal-energy signal groups, each containing two antipodal signals, such that the signals from different groups are orthogonal.

Recently, M-ary biorthogonal modulation has been presented for ultrawideband communication systems [3], [4]. This modulation scheme achieves an improved performance with less detection complexity by locating two antipodal signals on each orthogonal domain and, hence, occupying exactly half of the geometric space of M-ary orthogonal signals. The symbol error probability (SEP) and bit error probability (BEP) of coherent M-ary biorthogonal signals over additive white Gaussian noise channel (AWGN) were analyzed in detail in [2, pp. 198–203]. It was shown that these error probabilities are given in terms of onefold infinite range integrals, in which the integrands depend on higher order powers of the 1-D Gaussian Q-function. Such dependence does, in fact, complicate the mathematical analysis of the system average error performance over fading channels. To overcome this difficulty, Beaulieu and co-workers [7], [8] proposed the use of alternative representations given in terms of finite range integrals, which enabled the analytical evaluation of average error performance of 6-ary and 8-ary biorthogonal signals over Rayleigh fading channels.

In [5] and [6], expressions for the system average error performance were derived for an arbitrary number of signals M over independent and identically distributed (i.i.d.) Nakagami-m and Ricean fading channels, respectively, assuming maximal ratio diversity combining (MRC). The analysis in [5] and [6] was mainly based on reexpressing the system conditional error performance in a nonfading AWGN channel in order to make the argument of the Gaussian Q-function, which has power proportional to M, independent of the received combined instantaneous signal-to-noise ratio (SNR). However, the final results obtained in [5] and [6] require the evaluation of infinite integrals, in which the integrands still contain high powers of the Gaussian

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