Asian Journal of Computer Science And Information Technology 4: 9 (2014) 76 - 82

Contents lists available at www.innovativejournal.in

Asian Journal of Computer Science And Information Technology

Journal Homepage: http://innovativejournal.in/ajcsit/index.php/ajcsit

ISSN 2249 - 5126

Research

DISTRIBUTED DYNAMIC CHANNEL IN TDMA MOBILE COMMUNICATION SERVICES

Y Durga Bhavani*, R V Krishore Kumar

Sri Mettapalli College of Engineering, Guntur, Andhra Pradesh

Contents lists available at www.innovativejournal.in

INNOVATIVE JOURNAL

Asian Journal of Computer Science And Information Technology

Journal Homepage: http://innovativejournal.in/ajcsit/index.php/ajcsit

AJCSIT

ISSN 2249 - 5126

Research

DISTRIBUTED DYNAMIC CHANNEL IN TDMA MOBILE COMMUNICATION SERVICES

Y Durga Bhavani*, R V Krishore Kumar

Sri Mettapalli College of Engineering, Guntur, Andhra Pradesh

ARTICLE INFO

Corresponding Author:
Y Durga Bhavani
Sri Mettapalli College of Engineering,
Guntur, Andhra Pradesh

Keywords: - Dynamic channel assignment, mobile communication, resource allocation, time-division multiple-access (TDMA), wireless communication.

crossref MEMBER CROSSREF.ORG THE CITATION LINKING BACKBONE

DOI:http://dx.doi.org/10.15520/ajcsit.v4i9.10

ABSTRACT

Dynamic channel assignment (DCA) has been a topic of intense research for many years, and a variety of DCA algorithms have been proposed. Nonetheless, some important issues have been neglected because of the complexity involved in their study. In particular, the impact of user motion on the performance of DCA systems has not received enough attention. In this paper, we quantify the impact of motion on the capacity and cost—in terms of average number of reassignments per call—of a variety of representative distributed fixed-power DCA algorithms. A novel adaptive algorithm especially suited for mobility environments is proposed which achieves high capacity while controlling the reassignment rate. We also prove that most of this capacity can be effectively realized with a reduced number of radio transceivers per base station. Finally, we evaluate the degradation associated with the use of estimates of local-mean signal and interference levels—obtained by averaging instantaneous measurements—in-stead of the actual local-mean values.

I. INTRODUCTION

DYNAMIC channel assignment (DCA) for frequency- and time-division multiple-access (FDMA/TDMA) systems has been a topic of intense research for many years [1]–[4]. As a result, a variety of algorithms have been proposed to the extent that low-tier systems such as CT2 [5], Personal handy phone System [6], and Digital Enhanced Cordless Telecommunications [7] implement simple DCA algorithms. DCA allows for a much more efficient use of the available spectrum—an increasingly scarce and expensive resource—and eliminates the burden of costly frequency planning, which becomes a formidable task in systems with a very large number of base stations (BSs). De-spite the effort devoted to investigating DCA algorithms, some important issues have been neglected because of the complexity involved in their study. In particular, the impact of user motion and the effects of imperfect signal and interference averaging are topics that have not received enough attention. These questions, not critical in fixed channel assignment (FCA) systems, have a direct impact on the performance of DCA schemes. Without their inclusion, any comparison between DCA and FCA might be distorted. In this contribution, we address these issues by means of large-scale computer simulations.

II.THE CHANNEL ASSIGNMENT PROBLEM

The problem of finding the assignment that can serve a certain distribution of users with the least number of channels for a given set of constraints has received a great deal of attention [10], [11]. Unfortunately, this general problem is NP-complete. Mathematical approaches have to either make simplifying assumptions or focus on solutions that can be computed in a reasonable time [12]–[15]. As a result, these methods generally make no distinction between users within a given cell. One would expect that total or partial knowledge of the position of every user within its cell could be exploited to achieve much tighter packing [16].

With DCA, all channels are placed in a common pool and dynamically assigned according to some strategy. Traffic-adaptive DCA algorithms assign channels to different cells depending on their respective loads and hence can alleviate traffic hot spots, but they fall short of exploiting user location [19]. Reuse distances are still fixed a priori. Interference-adaptive algorithms, on the other hand, collect signal and interference measurements that relate to the position of users. By adjusting their reuse distances according to that information, they can push capacity to higher levels. With interference-adaptive DCA, reuse distances are variable, and thus the channel assignment algorithms them-selves have to protect active users from new assignments. There-fore, the problem of finding the most appropriate channel for a new user can be broken down into two distinct problems.

Admission control problem: The system has to determine the subset of idle channels on which the new user can coexist with the users already on those channels. To do so, the mutual path gains for the entire set of co-channel users *including* the new candidate user have to be known for every channel. This problem can only be resolved by centralized algorithms, which are impractical [20]–[22].

Selection problem: The system has to select—based on some strategy—a channel from those, if any, that meet the admission criterion. Knowledge of signal and interference levels at the new user's location suffices, and hence distributed approaches are feasible.

III. DCA CHANNEL MANAGEMENT

A control channel (CCH) facilitates the implementation of DCA and becomes a reference resource for the entire system [3]. It also allows mobiles to locate BSs for initial access and handoff. Therefore, we construct our algorithms with the assumption that a CCH exists. In addition, system-wide synchronization is desirable with DCA, for it simplifies the structuring of the CCH [3]. Accordingly, synchronization to the slot level is assumed throughout this paper.[3] With that, our analysis holds for both time- and frequency-division duplexes systems, and a traffic channel (TCH) corresponds to a pair of specific carrier/slot combinations for uplink and downlink

To determine whether a given user meets the required up-link and downlink threshold for initial access, reassignment, or handoff, interference measurements are performed by BS and mobile on the specific TCH and compared against the signal level. As the signal level is obviously unavailable on the TCH before the assignment, it has to be mapped from the CCH.[5] The thresholds chosen for our implementation were obtained by an iterative process and are summarized in Table I. Although the absolute performance of the various algorithms we discuss shows some sensitivity to the threshold choices, the relative performance is quite robust.

IV. UPLINK DOWNLINK BALANCE

Since the quality of a link is basically conditioned by its weakest component, a key aspect of any channel assignment algorithm is the balancing of uplink and downlink. With a few exceptions [3], [28], the issue of achieving balanced link performance has been overlooked in much of the DCA litera-ture—where the algorithms usually operate on either uplink or downlink exclusively—and even in the first systems that have implemented DCA. Besides differences in receiver sensitivity, transmit power, antenna diversity, etc., the factors contributing to link imbalance are as follows.

A proposed implementation of such an algorithm is one where each BS maintains a database with the state of all idle channels. Every time a channel has to be assigned, a shortlist containing the L best candidates—according to the uplink—is passed on to the mobile, which makes the final selection according to the downlink [3].[6] With this approach, the link balance is controlled by the shortlist size. Good results are obtained with $L = 6$– 8 channels [3], with shorter lists tending to favor the uplink and longer ones favoring the downlink.

Although user motion tends to destroy the balance so painstakingly obtained, balance is restored at every channel reassignment and handoff.

Table I Simulation Parameters And Data

BS Separation	1 Km
Traffic Channels	128
Propagation Exponent	α=4
Log-Normal Shadowing	σ=10 dB
Shadowing Correlation Distance	χ_s=50 m
Mean Call Duration	100 s
Antenna Diversity	2-Branch Selection
Transmit Power and Noise Floor	Calibrated for Average CNR=35 dB at Cell Corner
CINR Drop-out Level	$\gamma < \gamma_{drop}$=9 dB for 5 consecutive seconds
CINR Minimum (Reassign) Level	γ_{min}=12 dB
CINR Admission Level	γ_{new}=18 dB
CINR Readmission Level	γ_{re}=16 dB
Directed Retry Attempts	3 BSs (total)
Shortlist Size	L=8 or L=8+8
Hand-off Hysteresis Margin	4 dB
Confidence Interval	±0.1% at 3% with 99% Reliability
Speed (Pedestrians)	Uniform 0–5 Km/h
Speed (Vehicles)	Truncated Gaussian Mean=30 Km/h Std=10 Km/h Max=60 Km/h
Hybrid Traffic Profile	80% Pedestrians 20%Vehicles

V. MODELS

A. System Model

Antennas are unidirectional with two-branch selection diversity (all thresholds are pre-diversity). BSs do not transmit on idle channels. Good orthogonality between carriers is assumed, and thus adjacent channel interference is not considered. Initially, no limitation in the number of radio transceivers per BS is considered either.[7] The local-mean CINR is defined as

$$\gamma = \frac{C}{I + N} \tag{1}$$

with C the carrier power, N the in-band thermal noise, and I the co channel interference. Mobiles and BSs have equal receiver and transmitter performance, with the ratio between transmit power and noise floor such that the average carrier-to-noise ratio at a cell corner—with no interference—is 35 dB. Offered traffic has a uniform spatial distribution with Poisson arrival rates and exponentially distributed holding times with a mean of 100 s.

B. Propagation Model

The local-mean path gain between two stations (identical for uplink and downlink) is modeled [17], [29] as

$$G = K \frac{S}{d^{\alpha}} \qquad (2)$$

where K is a calibrated constant for the particular environment, d is the distance, α is the propagation exponent, and S is a shad-owing log-normal term with standard deviation $\sigma = 10$ dB. The spatial autocorrelation function for the shadowing process is a polynomial approximation to an exponential function [30] with a correlation distance $X_s = 50$ m.

C. Mobility Model

The mobility model is a random walk controlled by a "directionality" parameter δ, which determines how often the mobile makes a turn. When a call is originated, the user speed is as-signed, the directionality δ is selected with uniform probability in the range 0–0.5, and an initial direction is randomly chosen. The speed is maintained throughout the entire call. Every 10 s, there is a turning opportunity, and thus the user changes direction or not with probability δ. When a change of direction occurs, the new direction is chosen from a triangular distribution centered on the old direction. This way, small angle turns are more probable than large ones. Three categories of users are defined according to their speed.

Stationary users: No motion.

Pedestrian users: Speed uniformly distributed within 0-5 km/h.

Slow vehicles: Speed sampled from a truncated Gaussian with a maximum of 60 km/h.

Using these categories, in turn, we define three classes of traffic.

Stationary: For applications such as wireless local loop.

Pure pedestrian: Shopping centers, campus environments, etc.

Hybrid: 80% pedestrians, 20% vehicles (urban and sub-urban areas).

Computer Simulations

Simulations are performed on a wrap-around universe consisting of a 16 × 16 square grid of BSs with the parameters summarized in Table I. The universe is created prior to the simulations, and thus the different algorithms are compared on the exact same scenario. In any given simulation, data collection does not start until the system has been brought to steady state. The confidence interval for all blocking and dropping rates is approximately $\pm 0.1\%$ at 3% with 99% reliability.

VI.PERFORMANCE OF DISTRIBUTED DCA ALGORITHMS WITH USER MOTION

Using an FCA scheme with a reuse factor of 1/16 as a reference, we compare the performance of four representative distributed DCA algorithms when exposed to the three classes of traffic defined in Section V-C. Although many other schemes have been proposed [4], [31], most of them are in fact variations or combinations of the schemes we are about to analyze, which are chosen to portray distinct types of strategies.

A. Channel Segregation

In a channel segregation algorithm (CSA), each BS stores a table with a priority value for every channel [32]. Upon an ad-mission request, the BS evaluates the channel with the highest priority. If it does not meet the admission threshold, the priority of that channel is decreased and the next highest priority channel is examined. If it does meet the threshold, the channel is selected and its priority increased. The priority of a channel is also de-creased when a user occupying that channel is dropped. With this method, each BS acquires its favorite channels by learning how they are used by the other BSs.

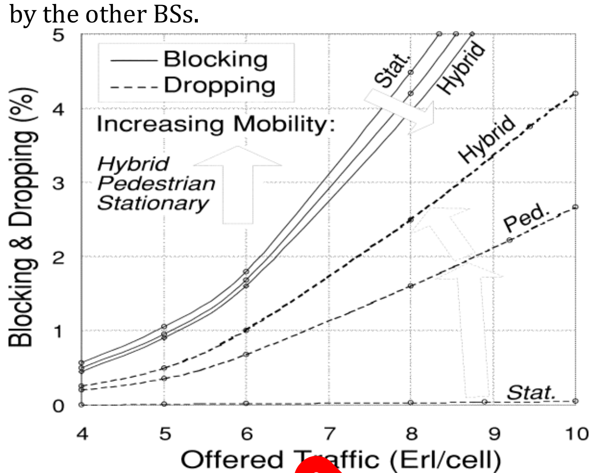
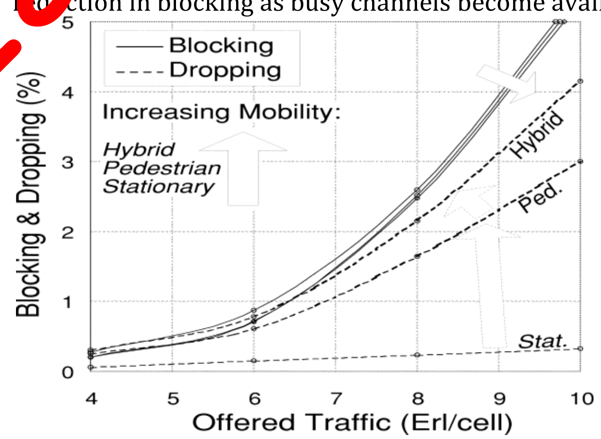


Fig. 1. Blocking and Dropping performance of CSA at different levels of mobility.

The performance of CSA—originally analyzed in [32] for stationary traffic only—is presented in Fig. 1. The blocking performance does not degrade with increasing mobility because every BS is able to resort to channels lower in the priority table. As a result, nonetheless, the segregation reuse structure is progressively destroyed, rendering users increasingly vulnerable to interference. Consequently, dropping increases so rapidly that, in fact, there is a slight reduction in blocking as busy channels become available



B Interference Minimization

Least interference algorithms (LIAs) are based on selecting always the most quiet channel [31]. Since they can be regarded as "greedy," they are particularly appropriate for open-access spectrum-sharing, with several operators using a common pool of channels. With motion factored in, however, blocking affects handoff users seeking a new BS as well as new users. Consequently, the dropping rate degradation caused by motion (Fig. 2) is even more dramatic than in CSA. Clearly, the system is unable to handle the increase in effective traffic associated with mobility as reassignment and handoff failure rates grow abruptly. Again, blocking actually decreases on account of the large number of dropped users.

C. Interference Maximization (Below Threshold)

The highest interference algorithm (HIA) tries to utilize the spectrum more compactly by selecting the most interfered channel below some level determined by the admission thresh-olds [31]. Evidently, one would expect this strategy to be poorly suited to high-speed users because of the need to continuously reassign them as they move. That is indeed the case, as seen in

Fig. 2. Blocking and dropping performance of LIA at different levels of mobility.

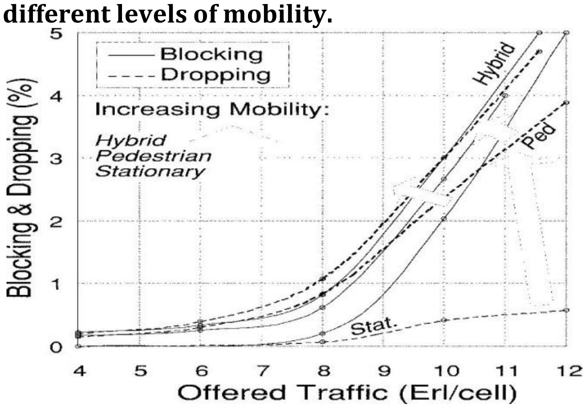
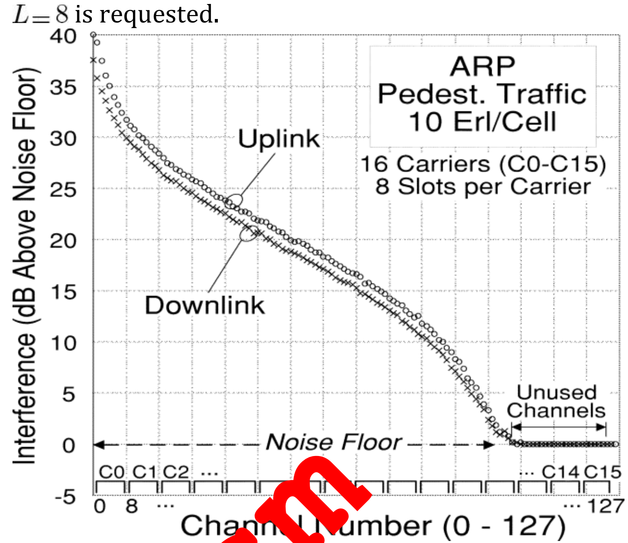
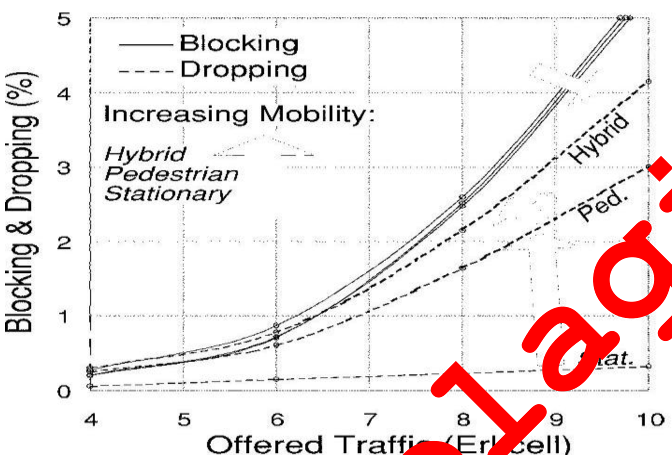


Fig. 3. Blocking and dropping performance of HIA at different levels of mobility.

Fig. 3, with significant increases in both blocking and dropping as mobility grows. Also, since all shortlist channels are chosen with an uplink CINR very close to the threshold, there is a no negligible probability that the downlink CINRs for all of them fall short of it. To minimize this probability, the shortlist is extended to $L=8+8$. If the mobile is unable to select any channel within the first set of $L=8$, a second set of $L=8$ is requested.





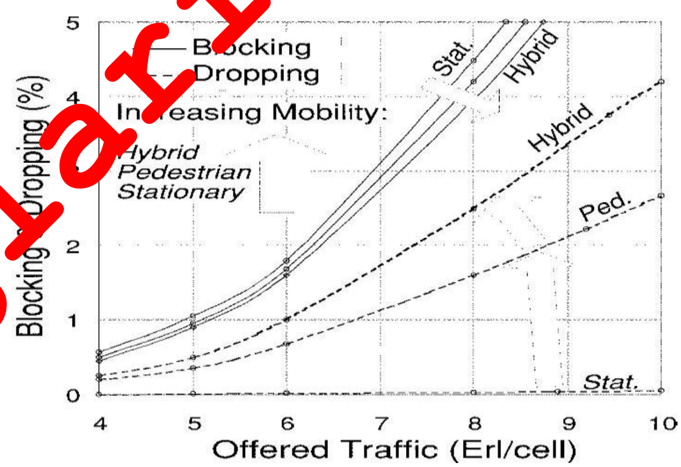


Fig. 4. Average channel interference upon initial assignment with ARP at 10 erlangs/cell

D. Autonomous Reuse Partitioning

The concept of reuse partitioning described in Section II, so effective with FCA, was extended to distributed systems in [33]. In the so-called autonomous reuse partitioning (ARP) algorithm, the channels are tested according to an ordering common to all cells, and the first idle one to meet the required threshold for both uplink and downlink is selected. They are assigned to users with weak signals, typically far from their BS. As the partitioning is achieved, the coverage area of every BS is divided into concentric rings—irregular in shape because of shadowing—each assigned to a distinct channel.

As traffic increases, idle channels are progressively activated until every channel is used. This point can be easily identified in Fig. 5, at any level of mobility, by a slope change in the blocking response as well as a sudden increase in dropping. Beyond that critical point, the system has serious difficulties allocating additional users, and thus performance degrades rapidly. User motion causes re-assignments and forces the system to activate additional channels earlier, so the critical point slides down.[8] although, like

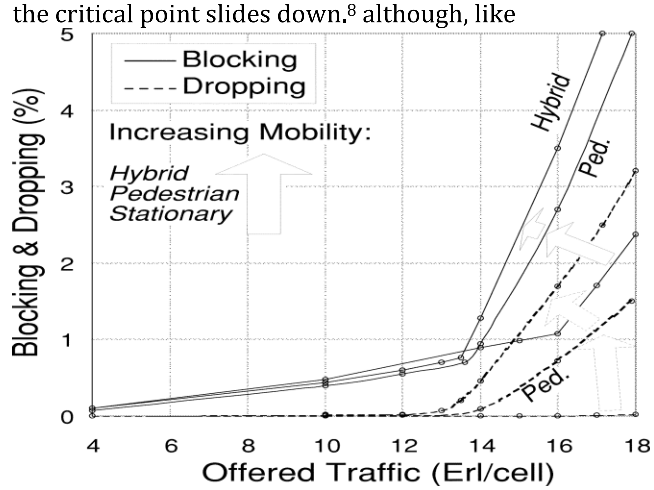


Fig. 5. Blocking and dropping performance of ARP at different levels of mobility.

HIA, ARP would not appear to be very well suited to high-speed users, it is in fact more robust because of the partitioning structure. Here, as users move, they roam into immediately adjacent ring areas corresponding to others channels whose levels of interference are only slightly different.

Since, as in HIA, the channels contained in the shortlist have an uplink CINR very close to the admission threshold, the short-list is also extended to $L = 8 + 8$.

E. Performance Comparison

The comparative blocking and dropping performances—in a pedestrian environment—of the algorithms described in the previous sections are depicted in Fig. 6 along with the FCA-16 reference. Uplink CINR cumulative distributions are shown in Fig. 7—downlink values show a similar trend—for a load of 10erlangs/cell. Notice how capacity can be directly related to the CINR distribution: high-capacity DCA algorithms are able to accommodate more users by arranging them so that their CINR is as close as possible to some target value (chosen to provide a comfortable margin above γ_{min}). This process is usually referred to as CINR balancing. Users above target do not experience any significant advantage, yet they diminish the system capacity by occupying channels that could have been assigned to other users in a more detrimental situation. Not surprisingly, its capacity falls even below that of CSA. Both HIA and ARP, on the other hand, achieve good CINR balance as expected. ARP, however, shows a much larger capacity, especially in terms of dropping. That is a direct result of the structured manner in which ARP packs users, which greatly reduces the probability that incoming users create excessive interference to active users [35]. Altogether, ARP outperforms all other algorithms presented, especially in terms of dropping.

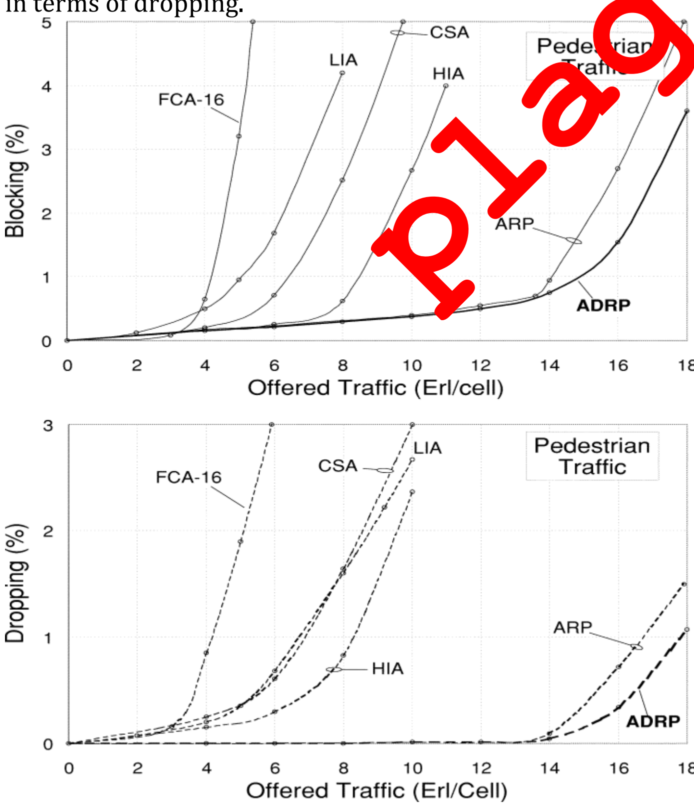


Fig. 6. Algorithm comparison in a pedestrian environment.

Shown in Table II is the average number of reassignments per call in a pedestrian environment. With LIA, the reassignment rate is very low. With CSA, the rate is also low, although it shows fast growth with traffic, confirming that the established segregation structure is being increasingly violated. HIA requires multiple re-assignments per call to sustain its non structured CINR balance, whereas ARP shows a moderate stable rate of reassignments.

VII.ADAPTIVE DISTRIBUTED REUSE PARTITIONING

ARP and related distributed reuse partitioning algorithms had previously been studied only in stationary environments [33]–[36], and their superior performance in those conditions has been reported [37]. In the previous section, it was shown that these techniques are robust and behave well also in mobility environments. In those conditions, however, it may be possible to further improve their performance.

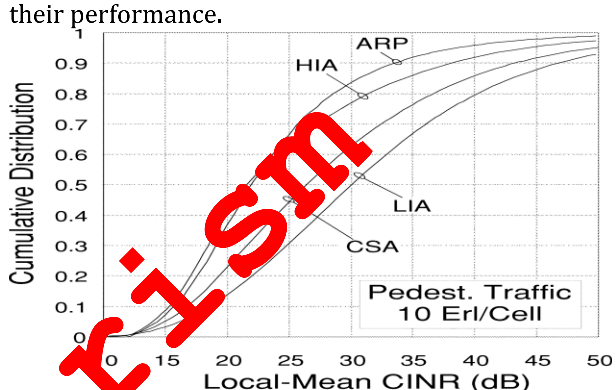


Fig. 7. Uplink CINR cumulatives at 10 erlangs/cell in a pedestrian environment.

TABLE II Average number of reassignments per call in a pedestrian environment. For adrp, the adaptive threshold is also shown. For all others, = 18 db

Traffic (Erl/Cell)	6	10	14
LIA	0.08	0.14	0.18
CSA	0.31	0.42	0.5
HIA	1.26	1.26	1.22
ARP	0.67	0.67	0.69
ADRP (γ_{new})	0.34 (24 dB)	0.49 (21.5 dB)	0.87 (18.1 dB)

With motion, the pattern distortion is much more severe, and users are likely to roam out of the partitioning ring corresponding to their channel. Reassignments, however, are only triggered when $\gamma < \gamma_{min}$, that is, when the CINR drifts toward too low a value. A more aggressive channel management policy could preserve the partitioning patterns by reassigning users every time they roam onto an adjacent ring regardless of whether that corresponds to a CINR drift toward too low or too high a value.

On the other hand, it has been shown that when ARP operates below its critical point—at low or moderate traffic values—it only utilizes a portion of the available channels. According to Fig. 4, the usage is 82% at 10 erlangs/cell in a pedestrian environment. With more channels in use, the same amount of interference is distributed over a broader bandwidth.[9] In our ADRP algorithm, every BS periodically adjusts its own admission thresh-olds by monitoring the activity on the lowest channel in the set as follows.

1) If no interference is detected on that lowest channel, the admission and readmission thresholds are increased by $\Delta\gamma = 0.1$ dB; otherwise, they are decreased by $\Delta\gamma = 0.1$ dB.

2)A maximum excursion of 6 dB is allowed ($18 \le \gamma_{new} \le 24$ dB, $16 \le \gamma_{re} \le 22$ dB).

The performance of the ADRP algorithm is displayed in Fig. 6 and in Table II along with the other algorithms. Besides some additional capacity gain with respect to ARP (7–8% at 3% blocking), the algorithm shows a reassignment rate more logically related to the system load: at low traffic values, reassignments are occasional (0.34 reassignments per call at 6 erlangs/cell), whereas in more congested conditions, reassignments are more frequent (0.87 at 14 erlangs/cell). Also shown in Table II is the adaptive admission threshold γ_{new} used by ADRP to control the reassignment rate. Also recall that by tightening the upper threshold γ_{max}, more capacity could be obtained in trade for an overall higher reassignment rate.

At the same time, DCA algorithms rely entirely on signal, interference, and CINR local-mean levels, which have to be estimated by low-pass filtering their instantaneous values. The quality of these estimates depends on the mobile speed and the dimension of the averaging window. This window must be long enough to average out fast-fading fluctuations, yet sufficiently short to track the shadowing variations. Interestingly, the shape of the averaging window is not a primary factor [38], and thus we choose to employ a simple rectangular window. The optimum *spatial* window length depends basically on X_s measured in wavelengths and on σ [38]. Unfortunately, the correspondence between this optimum length and the averaging *time* window is determined by the mobile speed, which is a parameter that is very difficult to evaluate. Measuring and tracking the velocity of mobiles in real time constitutes a topic of active research [39]. If such information were available, the estimation

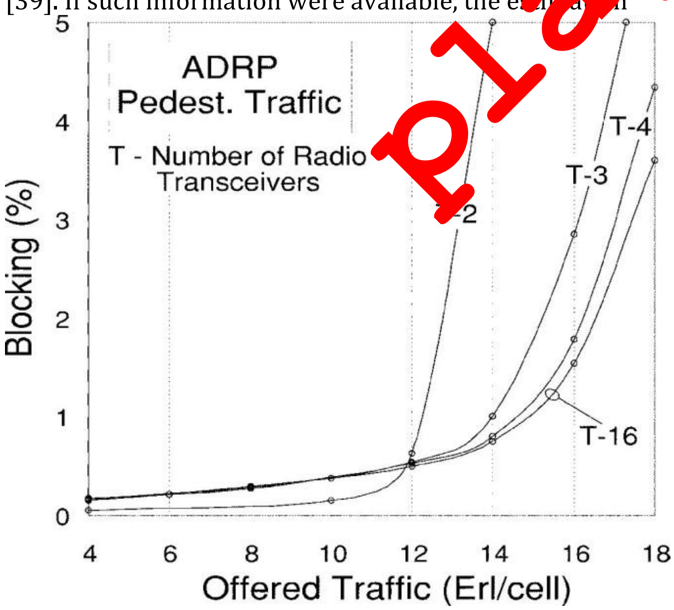


Fig. 8. Blocking performance of ADRP versus number of radio transceivers in a pedestrian environment.

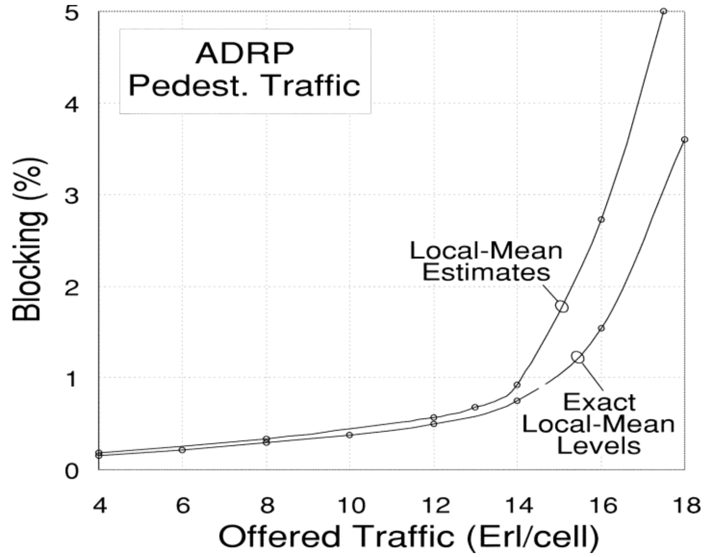


Fig. 9. ADRP performance degradation when exact local-mean levels are replaced by local-mean estimates with Rayleigh fades and a 500-ms averaging window at 1.9 GHz. No limit on transceivers.

In Fig. 9, we quantify the performance degradation of the ADRP algorithm in a 1.9-GHz pedestrian system with Rayleigh fading and local-mean estimates used instead of the actual local-mean values. At 3% blocking, the capacity loss is only 6%. Dropping, on the other hand, is basically unaffected because when a reassignment fails because of erroneous estimates, the system simply triggers a new attempt. The reassignment rates, on the other hand, increase by about 10%.

CONCLUSION

This paper has quantified the impact of user motion on the capacity and cost—in terms of average number of reassignments per call—of a variety of distributed fixed-power DCA algorithms. Comparative performance analysis of these algorithms has shown that the concept of CINR balance is essential in order to exploit the instantaneous position of users to achieve tight reuse distances and high capacity [34]. Distributed reuse partitioning algorithms are very effective at achieving a good degree of CINR balance. Within this class of algorithms, we have pro-posed a novel adaptive algorithm (ADRP) that further increases capacity by about 7–8% while significantly reducing the reassignment rate at low and moderate load levels. With respect to a conventional FCA system with a reuse factor of 1/16, a capacity 3.7 times higher (at 3% blocking) can be achieved with ADRP in pedestrian environments.

It has also been shown that most of this capacity can be realized effectively with a reduced number of radio transceivers per BS, despite the fact that local-mean estimates of signal and interference levels obtained by averaging instantaneous measurements are constrained by necessarily short temporal estimation windows and thus deviate from their actual local-mean values.

ACKNOWLEDGMENT

A. Lozano wishes to express his gratitude to Dr. B. Eidson at Conexant Systems and to Dr. T. Bourk at Silicon Wave for their helpful suggestions and support during the course of this research project.

REFERENCES

1. D. C. Cox and D. O. Reudink, "A comparison of some channel assign-ment strategies in large scale mobile communication systems," *IEEE Trans. Commun.*, vol. COM-18, pp. 190–195, Apr. 1972.
2. L. G. Anderson, "A simulation study of some dynamic channel assign-ment algorithms in a high capacity mobile telecommunication system," *IEEE Trans. Commun.*, vol. COM-19, pp. 1294–1302, Nov. 1973.
3. J. C.-I. Chuang, "Performance issues and algorithms for dynamic channel assignment," *IEEE J. Select. Areas Commun.*, vol. 11, pp. 955–963, Aug. 1993.
4. *IEEE Personal Commun. Mag.*, pp. 10–31, June 1996.
5. R. S. Swain and D. W. J. Holmes, "The digital cordless telecommunica-tions common air interface," *Br. Telecommun. Technol. J.*, vol. 8, no. 1, pp. 12–18, Jan. 1990.
6. "Digital European Cordless Telecommunications, Reference Docu-ment,", ETSI Doc. DTR RES-3001.
7. G. J. Foschini, B. Gopinath, and Z. Miljanic, "Channel cost of mobility," *IEEE Trans. Veh. Technol.*, vol. 42, pp. 414–424, Nov. 1993.
8. D. Lucatti, A. Pattavina, and V. Trecordi, "Bounds and performance of reuse partitioning in cellular networks," *Int. J. Wireless Inform. Net-works*, vol. 4, no. 2, pp. 125–134, 1997.
9. K. N. Sivarajan, R. J. McEliece, and J. W. Ketchum, "Channel as-signment in cellular radio," in *Proc. IEEE Vehicular Technology Conf. (VTC)*, May 1989, pp. 920–924.
10. X.-R. Cao and J. C.-I. Chuang, "A set theory approach to the channel assignment problem," in *GLOBECOM'94*, Dec. 1994, pp. 1647–1651.
11. D. Kunz, "Channel assignment for cellular radio using neural networks," *IEEE Trans. Veh. Technol.*, vol. 40, no. 1, pp. 188–193, 1991.
12. R. A. Leese, "A unified approach to the assignment of radio channels on a rectangular hexagonal grid," *IEEE Trans. Veh. Technol.*, vol. 46, pp. 968–980, Nov. 1997.
13. S. Sarkar and K. N. Sivarajan, "Hypergraph models for cellular mo-bile communication systems," *IEEE Trans. Veh. Technol.*, vol. 47, pp. 460–471, May 1998.
14. C. Y. Ngo and V. O. K. Li, "Fixed channel assignment in cellular radio networks using a mofified genetic algorithm," *IEEE Trans. Veh. Technol.*, vol. 47, pp. 163–172, Feb. 1998.
15. Z. J. Haas, J. H. Winters, and D. S. Johnson, "Simulation results of the capacity of cellular systems," *IEEE Trans. Veh. Technol.*, vol. 46, pp. 805–817, Nov. 1997.
16. W. C. Jakes, *Microwave Mobile Communications*. New York: Wiley, 1974.
17. S. W. Halpern, "Reuse partitioning in cellular systems," in *Proc. IEEE Vehicular Technology Conf. (VTC)*, 1983, pp. 322–327.
18. J. Zander and H. Erikson, "Asymptotic bounds on the performance of a class of dynamic channel assignment algorithms," *IEEE J. Select. Areas Commun.*, vol. 11, pp. 926–933, Aug. 1993.
19. R. Nettleton and G. Schloemer, "A high capacity assignment method for cellular mobile telephone systems," in *Proc. IEEE Vehicular Technology Conf. (VTC)*, May 1989, pp. 359–367.
20. K. N. Sivarajan, R. J. McEliece, and J. W. Ketchum, "Dynamic channel assignment in cellular radio," in *Proc. IEEE Vehicular Technology Conf. (VTC)*, 1990, pp. 631–635.
21. N. Bambos and G. J. Pottie, "Power control based admission policies in cellular radio networks," in *GLOBECOM'92* , 1992, pp. 863–867.
22. G. J. Foschini and Z. Miljanic, "Distributed autonomous wireless channel assignment algorithm with power control," *IEEE Trans. Veh. Technol.*, pp. 420–429, Aug. 1995.
23. N. Bambos, "Toward power-sensitive network architectures in wireless communications: Concepts, issues, and design aspects," *IEEE Personal Commun.*, vol. 5, pp. 50–59, June 1998.
24. C. J. Hansen, C. Wang, and G. J. Pottie, "Distributed dynamic channel resource allocation in wireless communication systems," presented at the 28th Annual Asilomar Conf. Signals, Systems and Computers, Oct. 1994.
25. N. Bambos, S. C. Chen, and G. J. Pottie, "Radio Link admission algo-rithms for wireless networks with power control and active link quality protection,", UCLA-ENG-94–25, 1994.
26. B. Eklundh, "Channel utilization and blocking probability in a cellular mobile telephone system with direct retry," *IEEE Trans. Commun.*, vol. COM-32, pp. 329–337, Apr. 1986.
27. D. C. Cox, "Universal digital portable radio communications," *Proc. IEEE*, pp. 436–477, Apr. 1987.
28. M. Gudmunson, "Correlation model for shadow fading in mobile radio systems," *Electron. Lett.*, vol. 27, no. 23, pp. 2145–2146, 1991.
29. M. M.-L. Cheng and J. C.-I. Chuang, "Performance evaluation of dis-tributed measurement-based dynamic channel assignment in local wire-less systems," *IEEE J. Select. Areas Commun.*, vol. 14, pp. 698–710, May 1996.
30. Y. Akaiwa and H. Andoh, "Channel segregation—A self-organized dy-namic channel allocation method: Application to TDMA/FDMA micro-cellular systems," *IEEE J. Select. Areas Commun.*, vol. 11, no. 6, pp. 949–954, 1993.
31. T. Kanai, "Autonomous reuse partitioning in cellular systems," in *Proc. IEEE Vehicular Technology Conf. (VTC)*, 1992, pp. 782–785.

How to cite Article: R V Krishore Kumar, Y Durga Bhavani. Distributed Dynamic Channel in TDMA Mobile Communication Services. **Asian Journal of Computer Science and Information Technology**, [S.l.], v. 4, n. 9, p. 76-82, nov. 2014. ISSN 2249-5126. Available at: <http://innovativejournal.in/ajcsit/index.php/ajcsit/article/view/10>. Date accessed: 15 Nov. 2014. doi:10.15520/ajcsit.v4i9.10.

Distributed Dynamic Channel Assignment in TDMA Mobile Communication Systems

Angel Lozano, *Member, IEEE*, and Donald C. Cox, *Fellow, IEEE*

***Abstract*—Dynamic channel assignment (DCA) has been a topic of intense research for many years, and a variety of DCA algorithms have been proposed. Nonetheless, some important issues have been neglected because of the complexity involved in their study. In particular, the impact of user motion on the performance of DCA systems has not received enough attention. In this paper, we quantify the impact of motion on the capacity and cost—in terms of average number of reassignments per call—of a variety of representative distributed fixed-power DCA algorithms. A novel adaptive algorithm especially suited for mobility environments is proposed, which achieves high capacity while controlling the reassignment rate. We also prove that most of this capacity can be effectively realized with a reduced number of radio transceivers per base station. Finally, we evaluate the degradation associated with the use of estimates of local-mean signal and interference levels—obtained by averaging instantaneous measurements—instead of the actual local-mean values.**

***Index Terms*—Dynamic channel assignment, mobile communication, resource allocation, time-division multiple-access (TDMA), wireless communication.**

I. Introduction

DYNAMIC channel assignment (DCA) for frequency- and time-division multiple-access (FDMA/TDMA) systems has been a topic of intense research for many years [1]–[4]. As a result, a variety of algorithms have been proposed to the extent that low-tier systems such as CT-2 [5], Personal Handyphone System [6], and Digital Enhanced Cordless Telecommunications [7] implement simple DCA algorithms. DCA allows for a much more efficient use of the available spectrum—an increasingly scarce and expensive resource—and eliminates the burden of costly frequency planning, which becomes a formidable task in systems with a very large number of base stations (BSs). Despite the effort devoted to investigating DCA algorithms, some important issues have been neglected because of the complexity involved in their study. In particular, the impact of user motion and the effects of imperfect signal and interference averaging are topics that have not received enough attention. These questions, not critical in fixed channel assignment (FCA) systems, have a direct impact on the performance of DCA schemes. Without their inclusion, any comparison between DCA and FCA might be distorted. In this contribution, we address these issues by means of large-scale computer simulations.

We define capacity as the traffic that can be served per BS at a certain level of quality—measured in terms of blocking and dropping rates—with a given number of channels. In the literature, blocking and dropping are often conveniently combined into a single metric, but that hides the ratio between the two. Since the relative importance of either one is subjective, we prefer to keep them separate and consider dropping to be more severe than blocking. At the same time, we define the "cost" of a DCA strategy as the average number of reassignments per call it requires.

The impact of user motion was investigated in [8] and [9] for FCA, although without interference considerations, only from the perspective of the increase in effective traffic caused by handoff. To the best of our knowledge, a more thorough analysis such as the one we undertake here has not been presented.

This paper is organized as follows. Section II discusses the benefits of DCA and justifies the need for both admission and reassignment control. Section III presents a distributed channel management approach that intends to perform such functions. In Section IV, the balance of uplink and downlink is addressed. Section V describes the simulation models. In Section VI, a performance comparison—including user motion—of several distributed DCA strategies is presented. Finally, Section VII proposes a novel algorithm especially suited for mobility environments.

II. The Channel Assignment Problem

The problem of finding the assignment that can serve a certain distribution of users with the least number of channels for a given set of constraints has received a great deal of attention [10], [11]. Unfortunately, this general problem is NP-complete. Mathematical approaches have to either make simplifying assumptions or focus on solutions that can be computed in a reasonable time [12]–[15]. As a result, these methods generally make no distinction between users within a given cell. One would expect that total or partial knowledge of the position of every user within its cell could be exploited to achieve much tighter packing [16].

When the number of channels is a given, the traditional FCA approach is to establish a reuse pattern determined by a reuse distance selected a priori [17]. FCA does not take advantage of user positioning, and thus the channels get assigned to cells and not to users. The reuse distance is conservatively chosen to ensure that any set of cochannel users can coexist with high probability regardless of their location. To exploit mobile positions with FCA, the concept of reuse partitioning can be adopted [18]. Reuse partitioning consists of dividing the total set of channels into several disjoint groups so that every group is reused with a different distance and every cell is assigned a number of channels from each group. Users with strong signal levels can tol-

Manuscript received February 8, 1999; revised December 13, 2001.

A. Lozano is with Bell Laboratories, Lucent Technologies, Holmdel, NJ 07733 USA (e-mail: aloz@lucent.com).

D. C. Cox is with the Center for Telecommunications, Stanford University, Stanford, CA 94305 USA.

Digital Object Identifier 10.1109/TVT.2002.802969