FUZZY LOGIC BASED DYNAMIC CHANNEL ASSIGNMENT

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Abstract: *In this paper, a class of dynamic channel assignment (DCA) algorithms referred to as the Fuzzy Distributed DCA (FDDCA) is presented. From decision point of view, conventional DCA algorithms are global and crisp decision makers. Decision of TO or NOT TO assign a channel for an incoming call is a crisp logic evaluation over a set of crisp system constraints. Complex logic operations are normally required to achieve the performance bound, resulting in increased cost and delay. In contrast, FDDCA algorithms are soft decision makers and the decision making is distributed. Every base station is responsible for making decisions of assigning channels for incoming calls. Fuzzy logic is employed as the decision making logic. Interference constraints are softened and treated as fuzzy sets characterized by membership functions. The algorithm was tested on the example by Sivarajan et. al. of Caltech [3], and is shown to outperform crisp DCA algorithms in throughput capacities, especially within the practical range of 1-5% blocking.*

I. INTRODUCTION

Dynamic Channel Assignment strategies (DCA) have been recognized as promising approaches for efficiently utilizing limited spectrum over Fixed Channel Assignment (FCA) strategies in FDMA/TDMA mobile communication systems. There are considerable amount of publications on this subject showing that DCA can outperform FCA in terms of throughput capacities under the condition of *non-uniform heavy traffic* [1-4].

Most DCA algorithms appeared on publications are based on *channel searching methods* subjected to sets of crisp constraints related to radio interferences. These constraints are represented by a *separation matrix* (or *compatibility matrix*) or, in equivalent, by a collection of v-*cliques* [3], where v are integers. Radio interferences can vary greatly from cell to cell. The normal practice is to set the constraints under the assumption of worst case on mobile location and propagation conditions [4]. The practice can result in large capacity penalty. Considerable margin is observed in the design of *signal to interference ratio (S/I)*. In order to achieve the theoretical bound, algorithms that can yield globally optimal solution, such as the MAXIMUM PACKING (MP) algorithm and the CALBOUND algorithm [3-5], can be used. Both methods require centralized computations and global information exchanges between all base stations (ports). This high complexity can result in intolerable call setup delays especially when the network size is large.

Heuristic based searching methods are proposed to alleviate the vast computational overheads in exchange of locally optimal solution. Artificial neural networks (ANN) based computational methods have been formulated by Kunz on DCA problems [6]. Kunz used a Hopfield model where the computation methodology is based on the principle of mutual inhibitions. The number of neurons in the network is equal to the product of the number of channels and the number of base stations. The strength of inhibitions is proportional to the incoming traffic rate, and inversely proportional to the distance of base stations and spectral distance of channels. The neural network is massively mutually-connected to represent the co-site, co-channel and adjacent channel constraints. When the ANN size (number of neurons) is small to moderate, the ANN algorithm can always converge to a locally optimal solution. When the ANN size is large, ANN can be inhibitively slow. Also there is no guarantee of the convergence to a correct solution in compliance with the compatibility constraints. Thus, DCA algorithm using ANN method is confined to DCA problems of small sizes.

The channel search methods presented above aim at globally optimizing the throughput capacity and thus require centralized computations which involve massive information exchange between all base stations. As computational complexities increase in a faster pace than network size, DCA algorithms that require centralized planning will eventually become infeasible. Chuang in [7] introduced a measurement based quasi-DCA algorithm with an aim to distribute the decision making. Instead of using system description parameters such as separation matrices or v-cliques, Chuang's algorithm takes into the account of actual propagation and interference conditions, both being obtained by measurements. Every base station takes turn to make autonomous decision of selecting the least interfered channel. With the transmitter off, the receiver at a base station will scan and measure the signal power of every channel. The channel that has the least signal power (i.e. least interference) is allocated to that base station. The algorithm is simple, distributed, and the service quality is also guaranteed. However this algorithm adopts a quasi fixed frequency plan and hence cannot achieve the spectral efficiency of more sophisticated DCA algorithms.

C. I and P. Chao of AT&T Bell Lab proposed a distributed DCA referred to as the Local Pack Dynamic Channel Assignment Scheme (LPDCA) [5]. The LPDCA algorithm can be viewed as a distributed search based DCA methods introduced earlier. Information exchange is local and within those base stations that can interfere each other "significantly" enough. Each base station keeps an augmented channel occupancy (ACO) table containing the current channel utilization information of every interfering station. Upon receiving a call, the base station will read the ACO table and select the channel that complies with the co-site constraint and co-channel constraints. If no qualified channel opened,

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the base station will either return a busy signal or execute the *m*-persistent polite aggressive policy [9,11] to borrow a channel from those interfering stations which have free channel opened. Decisions of allocating channel or executing the persistent policy are crisp. A station will broadcast messages to every interfering station if the station has successfully allocated a channel to a call, or has yielded a channel to one of the interfering station which executes the persistent polite aggressive policy. The algorithm is demonstrated to have good throughput performance as well as good adaptability to non uniform traffic patterns, such as isolated hot-spots and shaped hot spots.

The algorithm introduced in this paper can be viewed as an extension of the LPDCA scheme. Indeed, we will employ LPDCA scheme as a framework while fuzzy logic is adopted as the decision maker. The new algorithm is termed the Fuzzy Distributed Dynamic Channel Assignment (FDDCA) algorithm. Fuzzy logic is soft logic as the truth value of an entity is not restricted to either false (truth value is zero) or true (truth value is unity), but in a continuum of [0,1]. The value 0 implies totally false and 1 implies totally true. Intermediate values are interpreted as partially true *and* partially false. A value of 0.7, for example, can be interpreted as quite true. On the other hand, the value 0.1 implies rather false. Both true and false are not mutually exclusive in fuzzy logic. Indeed, softness of truth values is a more appropriate representation of determining if a given interference constraint is complied or violated. This in effect removes the imposition of worse case assumptions from the decision making of channel assignment. Since the conditions are soft, decision making with fuzzy logic is also soft. In other words, decision of TO or NOT TO assign a channel is represented by a truth value in [0,1] computed with fuzzy logic. The value 0 implies definitely NOT TO assign, and the value 1 implies definitely TO assign.

The FDDCA strategy takes into account of the following items:

- Cosite constraint (minimum channel separations within a site) and non-cosite constraints (minimum channel separations among two sites) are *soft* constraints. When the separation of two channels are too close, interference is heavy. However, interferences are proportionally decreased as the separation gets farther. Determination of constraint violation or compliance by a crisp thresholding is certainly not appropriate. One would also need to take into the account of time varying physical parameters such as relative positions of mobile units and ports, as well as short term and long term fading conditions. Thus, compliance or violation of the two constraints are more adequately represented by fuzzy truth values.
- In certain circumstances, users may prefer throughput over slight degradation in voice quality. Thus, when there is a high traffic rate in a particular site, it may be possible to *soft-violate* certain worst case electromagnetic compatibility constraints given that the voice quality can be maintained.

The FDDCA is formulated based on the consideration of two arguments stated above. We also consider the traffic density within each cell. By that we introduce the fuzzy concept of *hotness* to quantify the traffic density. We will also introduce the fuzzy concept of *usability* of every channel. The usability of a channel is a soft truth value based on a collective evaluation of the compliance/violation level to each constraint if the channel is to be assigned. The throughput performance of FDDCA has been studied via extensive simulations. We will show that the throughput of FDDCA is determined by fuzzy channel assignment schemes used. Simulations show that the throughput capacity can surpass that of the CALBOUND when the concepts of hotness and soft violation are implemented. Given the two concepts are implemented, simulation results show that the trunk quality, defined as the cumulative distribution of signal to interference ratio, is not degraded.

In the following section we will explain how the crisp values of cosite and non-cosite channel separations are soften. The FDDCA algorithm as well as the simulation criteria adopted in our work will be elaborated in order.

2. FDDCA ALGORITHM

2.1 Distributed database

At each base station, an augmented channel occupancy (ACO) table is maintained. As shown in Table I, the entries in the table are the current channel occupancy status of every interfering neighbor cells as well as the host cell, site i_o. Each row holds the channel occupancy information of an interfering cell. The *M* columns represent the *M* channels. An x mark in the *ij*th entry implies the *j*th channel is occupied at the *i*th cell. There are ν_{i_o} interfering base stations in the ACO, where $\nu_{i_o} < N$, N is the total number of base stations.

	Channels			
site	1	2	...	*M*
i_o		x		
i_1	x			x
:		x		
$i_{\nu_{i_o}}$	x			x

Table I. ACO table at site i_o

2.2 Fuzzy parameters

Physical parameters are mapped onto membership functions characterizing fuzzy concepts. The membership values, or the truth value, are fed to the *antecedent* section of the fuzzy rules. Inference logic is used to compute the truth value of the *consequent* of the rule after the overall truth value of the antecedent section is evaluated. In this paper, we will use the direct product of membership values as the evaluation method

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of the overall truth value of the antecedent section, and the MAX-product rule as the inferencing method. Details of fuzzy inferencing are given in [10].

We now proceed to elaborate the fuzzy concepts of *hotness* and *usability*. In the simplest form, hotness is defined as the ratio of offered traffic in a given cell to the total offered traffic. Since the importance of DCA strategy arises in the case of non-uniform heavy traffic, hotness parameters are used to depict the distribution of traffic in different cells. We first define the following notations to be used later:

ρ_i : the offered traffic in cell i,

λ_i : the call arrival rate in cell i, and

$1/\mu$: the mean call duration,

Since $\rho_i = \lambda_i/\mu$, thus hotness of a cell, h_i, is proportional to λ_i. We then proceed to define the concurrent *usability* of the channel f_k in site i, and the channel f_l in site j, as a membership function $\Im_{ij}$ of the spectral distance between two channels.

$$u_{ij}(f_k, f_l) = \Im_{ij}(|f_k - f_l|) \tag{2.1}$$

for $i,j = 1,2,\ldots, N$, where N is the total number of cells in the network, and $k,l = 1,2,\ldots, M$, where M is the number of channels. With (2.1), we define the fuzzy compatibility matrix:

$$\begin{bmatrix} \Im_{11} & \Im_{12} & \ldots & \Im_{1N} \\ \Im_{21} & \Im_{22} & \ldots & \Im_{2N} \\ \vdots & \vdots & & \vdots \\ \Im_{N1} & \Im_{N2} & \ldots & \Im_{NN} \end{bmatrix} \tag{2.2}$$

Usability measures for the cases of crisp logic and fuzzy logic are shown in Fig. 1. Usability measure for the case of fuzzy logic can be viewed as a softening of that of crisp logic shown in Fig.1(a). The usability curve for fuzzy logic can take on any shape as long as the shape is meaningful to be interpreted. Choosing the right membership function is vital in obtaining good performance.

With these definitions, we now elaborate the FDDCA algorithm in terms of pseudo-code.

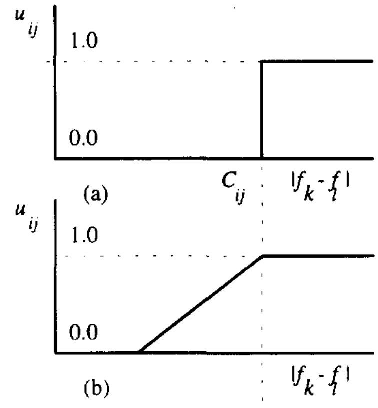

Fig. 1. Concurrent Usability of two channels in two sites for the cases of (a) crisp rule, and (b) Fuzzy rule. C_{ij} is the minimum separation in the crisp separation matrix.

2.3 FDDCA algorithm

On the arrival of a call request in the site i_o :

for each channel, f_k:k=1,2,...,M,

for each channel, f_l:l=1,2,...,M,

if f_l is being used in any of the site, i_n, in the ACO table, including i_o, compute $|f_k$-$f_l|$.

compute the corresponding usability index, $u_{i_o,i_n}(f_k, f_l)$ with the use of fuzzy separation matrix.

for each channel, f_k:k=1,2,...,M, compute the overall usability index using the product rule:

$$u_{i_o}(f_k) = \prod_{n=0}^{V_{i_o}} \prod_{l=1}^{M} u_{i_o,i_n}(f_k, f_l)\ ;$$ *where* V_{i_o} *is the number of interfering base stations in the ACO table.*

(2.3)

select the channel f_j with the best usability index.

if there are more than one channels with same usabilty index select the channel which has been engaged for the longest time.

feed the usability index and the hotness index to the fuzzy decision maker.

After obtained the suability and hotness figures, the decision to honor or block the call is determined by inferencing of a set of control rules stating the relationship of usability and hotness to the desirability to honor or block the call. The set of control rules used in this paper is as follows:

*R*1: if *usability* LOW , then BLOCK
*R*2: if *usability* HIGH, then HONOR

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*R*3: if *usability* MEDIUM *AND hotness* LOW, then BLOCK
*R*4: if *usability* MEDIUM *AND hotness* HIGH, thenHONOR

Two membership functions, LOW and HIGH, are set for the hotness index. And three membership functions, LOW, MEDIUM, and HIGH, are set for the usability index. Each of these membership functions are manually set. We will describe the selection of membership functions for some particular example in the next section.

3. SIMULATIONS AND RESULTS

3.1 Simulation Environment

The simulation assumed exponentially distributed inter-arrival time (Poisson arrival) and call holding time. A call request arrives to the cell i with a probability p_i .Hence the offered traffic in the ith cell is equal to $\rho_i = p_i\rho$, where ρ is the total traffic in the entire system. Blocked calls are assumed to be cleared. In order to assess the cumulative distribution of signal to interference ratio (S/I), within each cell 192 uniformly distributed user positions are considered. The distribution of call generation within a cell was assumed to be uniform. The received signal (interference) power was taken to be proportional to $1/d^4$, where d is the distance between the base station and the mobile unit. Non-cochannel interference was weighted by a factor <1.0. Weighting factors for adjacent channel interference in the simulation were 0.1, 0.01, 0.001, and 0.0001 for channels with spectral separations 1,2,3 and 4 respectively. Computation of S/I was carried out considering all users in the system at steady state.

The system simulation program generates an exponentially distributed random number with a pre-determined mean to decide upon the next call arrival time. Generation of random number for the call holding time is similar. An infinite population is assumed and thereby the arrival rate remains constant. When there is a call arrival, it is assigned to a particular site with the probability as mentioned above paragraph. Next the channel assignment routine is called. At each increment of the clock, on going calls are checked for any departure. If there is any departure, tied frequencies are released. (More details can be found in [3]. A different approach to system simulation is adopted in some other literature [8]).

3.2 The simulation and results

The example is adopted from [3], where N=21 and M=96. Non-uniform Spatial Distribution of traffic is assumed with distribution listed in Table II. The cell arrangement for the example is as in Fig. 2. The worst case channel separations (same as the crisp separations under conventional method) are, five for cosite, two for first tier cells, and one for second and third tier cells. For instance, $c_{77} = 5$, $c_{71} = c_{78} = 2$, $c_{72} = c_{79} = c_{73} = 1$. In FDDCA strategy, these values are softened, as depicted in Fig.3. The hotness was considered to be HIGH if it is greater than a threshold, T. Figures 4 and 5 show the performance of the FDDCA algorithm. The blocking performances of FDDCA with four different constraints are computed and contrasted with the results corresponding to FCA, and DCA algorithms, namely SIMPLE, MAXAVAIL,

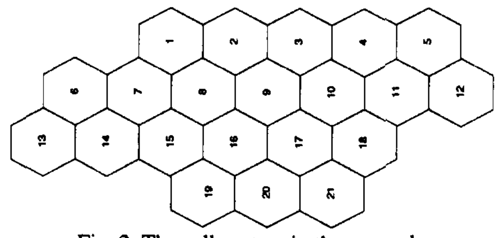

Fig. 2. The cell system in the example

i	p_i	i	p_i
1	0.0166	12	0.0312
2	0.0520	13	0.0644
3	0.0166	14	0.0312
4	0.0166	15	0.0748
5	0.0166	16	0.1185
6	0.0312	17	0.0582
7	0.0374	18	0.0166
8	0.1081	19	0.0208
9	0.1601	20	0.0270
10	0.0582	21	0.0166
11	0.0270		

Table II. Non-uniform traffic distribution

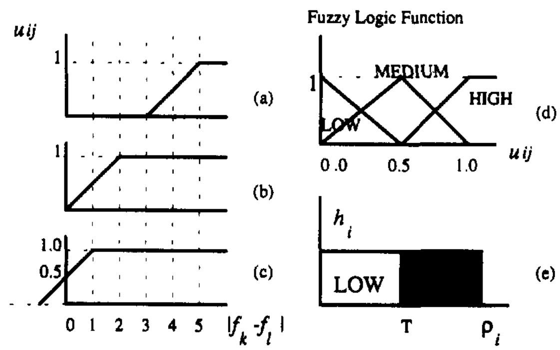

Fig. 3. Fuzzy channel separation functions, and logic functions for the example. (a), (b), and (c) give the usability index functions for C_{ij}=5, C_{ij}=2, *and* C_{ij}=1 respectively. (d)curves for logic levels LOW, MEDIUM, and HIGH as functions of u_{ij}. (e)hotness index

and CALBOUND, presented in [3]. The simulation conditions are same as that in [3]. The mean inter-arrival time was set at $180/\rho$ seconds, and mean call duration is 180 seconds. The threshold T for the schemes I, II, and III, is 0.1, 0.05, and 0.01 respectively, corresponding to the number of cells being marked as *highly hot* is 3, 8, and 21 respectively. Careful examination reveals that when a cell exhausts the channels with crisp logic, the FDDCA allows those hot sites to softly violate only one of the three electromagnetic (EM) constraints by at most one channel separation. Clearly, this soft violation scheme is activated only when the traffic is heavy. Indeed, as the traffic gets heavy, the throughput capacities of FDDCA can break away from that of CALBOUND. Note that by drawing the line of 1-5% blocking probability in Fig.4, only the CALBOUND and Schemes II and III remains in this range when the traffic is heavy. Both Schemes II and III outperform CALBOUND when the traffic increase is moderate. As in Fig. 5, CDF of S/I for cases with violations of EM constraints are close to those without such violations, and the quality is within the required range. It is interesting to note that at the tail end (first percentile) of the CDF curves, all cases result in almost the same performance. Obviously, the situation would be quite different if a softer rule were applied to permit base stations to assign channels more aggressively. However our results have shown that when the traffic increase is large, the softening strategies presented in this paper establish a methodology to improved throughput performance without increase of computational complexities.

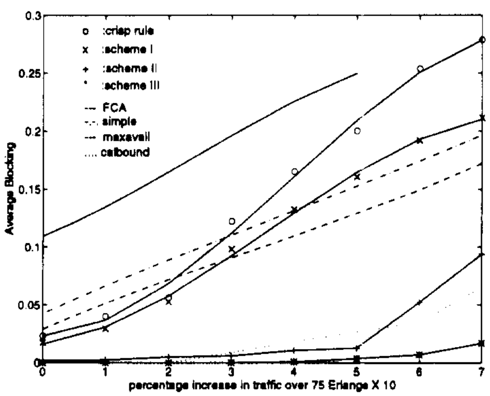

Fig. 4. Average Blocking vs. percentage increase in Traffic

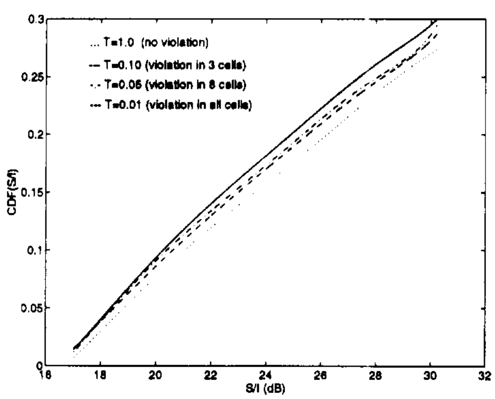

Fig. 5. Cumulative Distribution of S/I at steady state when total traffic, ρ=97.5 Erlangs.

4. Conclusion

In this paper, we present a distributive DCA scheme referred to as the fuzzy distributed DCA where fuzzy logic is employed for soft decision making . In contrast to most DCA algorithms where decision makings are crisp logic evaluation of sets of crisp interference constraints, the FDDCA scheme has demonstrated to have good throughput performance in scenarios of non-uniform heavy traffic. The fuzzy violations of EM constraints carried out in achieving such performance is shown to maintain adequate quality in terms of cumulative distribution of S/I ratio.

5. References

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